Empirical studies on R&D, innovation and the business cycle

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Empirical Studies on R&D, Innovation and the Business Cycle

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Chapter 1

Introduction

1.1 Motivation and background

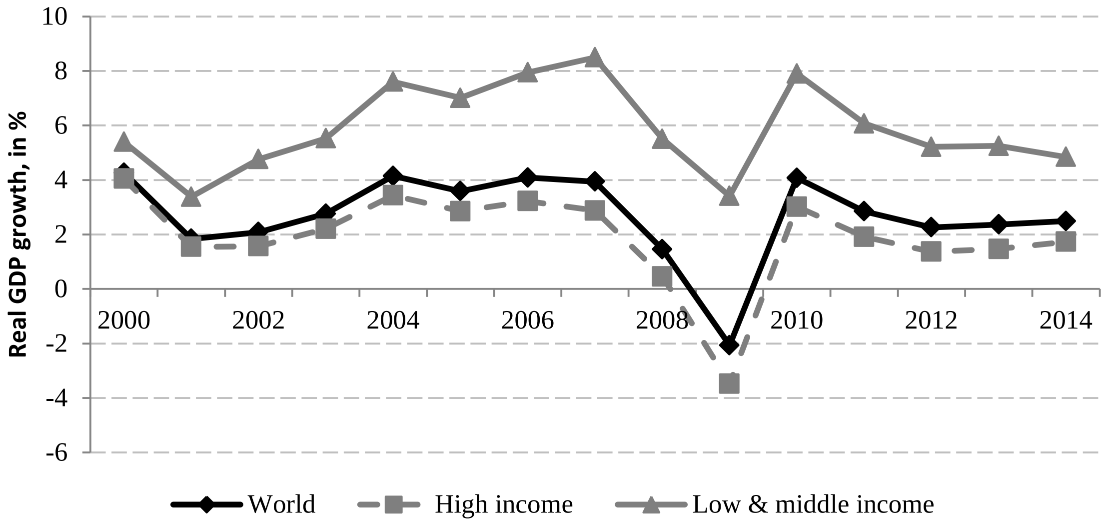
The world-wide economic development of the recent past has been very volatile. Since the bursting of the information technology bubble in 2001, the world's GDP growth increased from 1.8% in 2001 to a new peak of 4.2% in 2004 (see Figure 1.1). From 2004 on, the world's GDP growth stabilised at a level of about 4% until 2007. During this six-year expansion period particularly the low and middle income economies' average GDP growth substantially increased. At the end of the year 2007, the USA's housing market bubble burst that eventually caused a world-wide economic crisis unprecedented in the post-war era (IMF, 2009a; Grusky et al., 2011). The high income economies' GDP growth dropped by -6.4%-points during the years 2007 and 2009. The GDP growth of the low and middle income countries significantly slowed down by -5.1%-points within the same two-year period. The very short and strong expansion of 2010 could strengthen the world's economies. However, it has not been long enough to really stabilise the average growth prospects. Instead, the economies have moved towards a low growth path after 2010. Even the low and middle income countries have not been able to revive their high growth rates. This post-recession expansion period has been unusually short as compared to the average duration of expansions that followed other post-war recessions (IMF, 2009b).[1]

The recent business cycle development indicates the importance of understanding the mechanisms underlying long-term economic growth because "[…] the higher the long-run growth rate of an economy, the shallower the recession and the greater the amplitude of expansions" (IMF, 2009b, p. 104). This means, strengthening the long-term growth path is essential to prevent deep recession periods in the future. The key determinant for long-term economic growth is innovation (Aghion and Howitt, 2009). In principle, an innovation is the implementation of new or significantly improved products/services (product innovations) or processes (process innovations) or new organisational methods (organisational innovations) or new marketing methods (marketing innovations). From a macroeconomic perspective, innovation increases the total knowledge stock and enables technological change, thus future productivity growth (Romer, 1986, 1990; Aghion and Howitt, 1992). From a firm's perspective, innovating is an effective way to increase the firms' performance and competitiveness (see Hall, 2011, for an overview). For instance, new products enable firms to

[1] According to IMF (2009b), the average duration of expansion periods is about five years (21.75 quarters).

gain competitive advantages by opening up new markets or by improving their products' quality. Process innovations, instead, enable the innovators to enhance their production efficiency. Hence, process innovators can gain competitive advantages by the reduction of production costs and thereby prices.

Figure 1.1: Real GDP growth of the world and aggregated country groups, in %



Source: World Bank's World Development Indicators; author's own illustration.

Policymakers around the world are well aware of the importance of innovation as a key driver for the economies' competitiveness and long-run growth. For instance, in 2006, the Chinese government initiated a 15-year "Medium- to Long-Term Plan for the Development of Science and Technology". With this plan, the central government seeks to move China towards an innovation-oriented society by the year 2020 (Serger and Breidne, 2007). In 2009, the Obama Administration released "A Strategy For American Innovation". It was already updated two times, in 2011 and 2015, to emphasise the importance of innovation for the economic development (White House, 2009, 2015). This strategy provides an elaborate approach to ensure the USA's future prosperity by preparing the economy for the more intense global competition. The European Commission (EC) has incorporated its innovation focus in 2010 in its growth strategy "Europe 2020" (EC, 2012). It is a large-scale action plan the development of which was initiated to counteract the 2008/2009 recession and to eliminate Europe's structural weaknesses in terms of productivity growth and employment levels as compared with e.g. the United States. Europe 2020 considers research and innovation as central driving forces to achieve "smart, sustainable and inclusive growth". These are just examples of three of the most important economic areas of the world for a rising national orientation on innovation that policymakers have put on their agenda recently (OECD, 2014).

The fact that innovation determines long-term economic growth does not mean that it is independent of cyclical fluctuations. The development of new products or processes can be very expensive, in particular research-intensive products. The financing of those projects may be easier in economic booms. In a similar vein, the success of innovations, e.g. the sales of new products, may be higher in boom periods as well. For these reasons, a proper design of an innovation strategy should take the underlying business cycle dynamics into account. Prior economic research on the business cycle dependency of innovation has largely focussed on innovation investment. Two opposing effects have been identified in the theoretical literature, (i) the liquidity restraint effect and (ii) the opportunity cost effect. The former is based on the result that firms primarily finance their innovation activities by their own cash flow, the level of which strongly depends on the demand situation (see e.g. Hall, 1992; Himmelberg and

Petersen, 1994; Harhoff, 1998). The liquidity restraint effect implies pro-cyclical innovation investment, i.e. firms increase the amount spent on innovation during boom periods and decrease the amount during recession periods. In contrast, the opportunity cost effect predicts counter-cyclical innovation investment (see e.g. Bean, 1990; Aghion and Saint-Paul, 1998). Accordingly, production resources are underutilised in recessions as compared to boom periods and should therefore be provided for innovation activities. The corresponding empirical literature has mainly found innovation investment to be pro-cyclical (see e.g. Wälde and Woitek, 2004; Fabrizio and Tsolmon, 2014). The results of Aghion et al. (2012) support the pro-cyclicality but they also find evidence for counter-cyclicality in case firms do not face financial constraints. With regards to the cyclicality of innovation output, it is the firms' demand expectation and the risk of imitation that primarily determine the timing of innovation (see e.g. Shleifer, 1986; Barlevy, 2007). As demand is expected to be highest and the risk of imitation is expected to be lowest in boom periods, firms are expected to shift the timing of innovation output to economic booms. Pro-cyclical patterns could be found by Geroski and Walters (1995) and Fabrizio and Tsolmon (2014) but only Fabrizio and Tsolmon (2014) have directly estimated Shleifer's (1986) and Barlevy's (2007) predictions.

Policymakers should consider that the pro-cyclical pattern of innovation investment and output *per se* may not be sufficiently informative for them to draw policy conclusions. For instance, it is unclear whether the pro-cyclicality is in fact caused by financial constraints or whether it indicates that the marginal return to innovation investment is higher in booms than in recessions. It could also be that firms focus on new product development in boom periods, which may be more expansive than the development of process innovations. Firms may also invest more in product imitations than radical market novelties in recession periods. In a similar line of reasoning, does pro-cyclicality of innovation output imply that innovations introduced in recessions are less important than innovations implemented in boom periods?

To shed light on these and other related questions, empirical research is needed that goes beyond the mere cyclicality of innovation in- and output. This dissertation provides first evidence on the efficacy of firm-level innovation over the business cycle. It contributes to the field of innovation research and can be used as a basis for discussion.

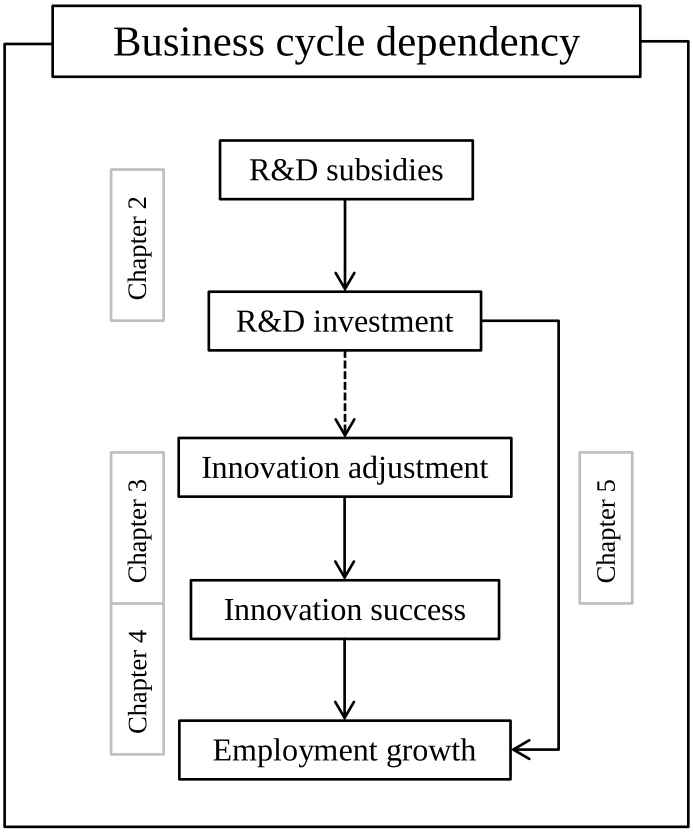
1.2 Dissertation outline

In this dissertation, I separately analyse the business cycle dependency of the different channels the relationship of innovation and firm growth is subject to. Figure 1.2 presents a graphical illustration of these different channels and the links to the respective thesis chapters. Whereas Chapter 2 examines the effect of R&D subsidies on firms' R&D investment over the business cycle, Chapter 3 investigates potential performance-enhancing effects due to increased innovation effort. Chapter 4 analyses the link between firms' innovation success and its related employment growth effects. Chapter 5 focusses on start-ups and their employment growth effects associated with R&D investment.

Chapter 2 focusses on the cyclical efficacy of R&D subsidies, which are a common type of government intervention aiming at fostering private R&D expenditures. The basic reason for publicly subsidising firms' innovation investment is that the amount of privately invested R&D is lower than the social optimum due to uncertainties and spillover risks (Arrow, 1962). Previous empirical studies find public funding to significantly increase firms' R&D expenditures (see Zúñiga-Vincente et al., 2014, for an overview). However, this additionality effect has not yet been examined as to its potential business cycle dependency. As e.g. the German government increased its public R&D funding during the recent recession, it is important to know for future policy interventions whether or not this type of counter-cyclical policy has been effective. For this reason, Chapter 2 investigates the impact of public R&D

subsidies on firms' R&D investment during the most recent economic crisis in Germany. In doing so, we focus on small and medium-sized enterprises (SMEs) because this type of firms is more business cycle sensitive than large firms and is also more important to job creation (OECD, 2009; Neumark et al., 2011). The analysis uses firm-level data of the Mannheim Innovation Panel (MIP) covering the period 2006 to 2010 and relies on propensity score nearest neighbour matching. Our analysis has three main results. First, we find that public R&D funding had a positive effect on SMEs' R&D investment amount over the observed period. Second, we find evidence for a crowding out effect of R&D subsidies for the crisis year 2009. This means, R&D investment of subsidised firms was lower than of non-subsidised firms in 2009. After the crisis, in 2010, when the German GDP almost reached its pre-crisis level, subsidies induced an additionality effect again. However, this was smaller than the additionality effect of the pre-crisis years. Third, additional tests indicate that this temporary crowding out effect was caused by reluctant innovation investment by the subsidy-receiving firms rather than by Germany's counter-cyclical innovation policy. The results suggest that public R&D subsidies for SMEs induce the desired additionality effect but that a counter-cyclical support scheme may need to be carefully designed.

Figure 1.2: Overview on the dissertation and its different chapters



Source: Author's own illustration.

Chapter 3 addresses the link between the adjustment of innovation investment on the performance of product innovations and its business cycle dependency. In particular, our target is to examine whether or not firms that increased their innovation expenses during the trough year of the most recent recession could increase their subsequent product innovation performance. We thereby analyse the efficacy of counter-cyclical investment behaviour of firms, while controlling e.g. for the firm-level impact of the recession and financial constraints. For this analysis, we rely on Fixed Effects models and use the Mannheim Innovation Panel (MIP) covering the period 2006 to 2012. We measure the product innovation success by the sales share of new-to-the-market products as well as by the sales share of new-to-the-firm products. Innovation adjustment is defined as an annual change of firms' innovation intensities. Its cyclical dependency is measured by interactions with three indicator variables representing a different category of growth (high, medium and low growth). The three growth categories are not only constructed by using annual GDP growth but also by annual industry-level sales growth to account for cyclicality within the firms' focal industry. We find that pro-cyclical innovation adjustment has a positive effect on subsequent innovation success. This relationship holds for the industry-based and GDP-based interaction terms. In addition, we find that counter-cyclical innovation adjustment is an effective way to stimulate innovation performance. The positive counter-cyclical effect is even stronger than the corresponding pro-cyclical effects. However, this stronger effect only holds in case the interaction terms are based on GDP growth.

Chapter 4 refers to the probably most relevant relationship in the context of innovation policy: The effect of innovation on employment growth. Indeed, there has been extensive research on this topic (see Pianta, 2005; Vivarelli, 2014 for overviews). However, it remains unclear whether the underlying mechanisms have a different effect depending on the business cycle period. Therefore, we investigate the employment growth effects of different types of innovations over the business cycle. Our specific target is to examine a potential resilience of innovators in case they have to face an economic slump. The analysis is based on the European-wide conducted Community Innovation Survey (CIS). In our sample, we include all available manufacturing firms of the whole set of 26 European countries. In total, the sample includes more than 200,000 firm-year observations of the period 1998 to 2010. The analysis' backbone is the structural model developed by Harrison et al. (2008, 2014). This model was particularly developed to investigate the labour-creating and labour-destructing effects of product and process innovations by using CIS data. We extend the model's standard specification and allow firm-level employment growth to also depend on organisational innovations. To account for cyclical differences, we construct four dummy variables by using country-specific GDP growth rates that enable us to split our sample into four different business cycle phases, i.e. upturn, boom, downturn, recession. We have four main findings. First, the net employment growth effect of product innovations is pro-cyclical. It turns out to be positive in all business cycle phases except for the recession case. Hence, the labour-creating effect exceeds the potentially labour-destructing effect in each business cycle period unless firms have to face a recession. Second, when faced with an economic slump, product innovations have an employment-preserving effect making the innovators more resilient than firms that have not introduced product innovations (non-product innovators). However, product innovators still cut jobs during recessions, on average. Third, this resilience of product innovators is, however, only found in SMEs but not in large firms. Fourth, process and organisational innovations tend to reduce firm-level employment growth during upturn and downturn periods, on average. This implies that arising productivity gains of old products displace labour demand. Our results suggest that product innovations are an important driving force as to firm-level job creation. They can even secure jobs during negative growth periods.

Chapter 5 has its focus on start-ups. This most dynamic type of firms is the most important job engine for an economy (EC, 2013; Haltiwanger et al., 2013). Start-ups are indispensable for technological change. Understanding the factors that influence their growth is crucial to stimulate an economy's competitiveness. Whereas previous empirical studies have identified and estimated the effects of several important indicators driving start-ups' growth, only a few analyses have focussed on the growth effect of innovation. These analyses' results are even difficult to compare because they use differing age groups to refer to "new firms" or "start-ups". Furthermore, the cyclical dependency of start-ups' employment growth induced by their innovation activities has not yet been examined. By using OLS, we investigate the job-creating effect of start-ups' R&D investment over the business cycle. In particular, we examine whether or not higher R&D investment during the 2008/2009 recession induced higher employment growth among start-ups. Our analysis is based on two comparable panel data sets of Germany and the USA. For the German sample we use the KfW/ZEW Start-Up Panel (SUP) and restrict it to firms founded in 2005. The US sample is provided by the Kauffman Firm Survey (KFS), which surveyed start-ups that were founded in 2004 only. Our samples cover the periods 2005-2012 (SUP) and 2004-2011 (KFS), respectively. We use the start-ups' R&D intensity as well as the annual change of R&D intensity. Further, we interact both variables by country-specific GDP growth and by country- and industry-specific gross value added growth (GVA) to estimate the business cycle dependency of the effect of R&D investment on employment growth. Our results indicate that start-ups' R&D investment increases the firms' employment growth. In addition, we find that counter-cyclical R&D investment is an effective way to increase employment growth. However, this counter-cyclical effect becomes only significant for manufacturing firms. The difference between the employment effects of the German and the US sample is that in the German sample it is the R&D intensity disclosing a counter-cyclical effect. In contrast, in the US sample, it is the annual difference of the R&D intensity reveals a significant counter-cyclical relationship to employment growth.

Chapter 6 summarises the different findings of this dissertation, highlights the most important implications and discusses the main limitations and directions for future research.

Chapter 2

The Impact of R&D Subsidies during the Crisis[2]

2.1 Introduction

The global economic crisis of 2008/2009 has severely affected the OECD economies. The unemployment rate has reached a post-war height of 8.5% in October 2009, the GDP declined by 4% in 2009 as compared to 2008 (OECD, 2012a), and long-term investments like innovation expenditures decreased significantly in a range of countries including Canada, Sweden and the UK (OECD, 2012b; Filipetti and Archibugi, 2011). Private sector innovation and research and development (R&D) activities substantially contribute to sustainable growth (Griliches, 1979; Grossman and Helpman, 1994; Aghion and Howitt, 2009; Doraszelski and Jaumandreu, 2013). Even a short-term decline or stagnation of these activities can have detrimental consequences in the long run. Policymakers are well aware of the importance of private sector R&D and also of the fact that private R&D spending tends to be lower than socially desirable, even in boom periods. For this reason, public support for R&D activities may be particularly important in times of an economic downturn. The investment in R&D projects is risky and the returns are uncertain and it takes a longer term before a firm can realise these returns. During recessions, not only those firms that face financial constraints are likely to reduce their investment in R&D (Schumpeter, 1939; Freeman et al., 1982). R&D investments may also be cut in response to a deteriorating demand situation in recession periods. Furthermore, it has been shown that the responsiveness of firms to policy initiatives is weaker in times of economic uncertainty (Bloom et al., 2007; Bloom, 2008). Uncertainty raises the real option value of investments, which makes firms more cautious concerning their R&D investment decisions during recessions. In order to prevent firms from reducing their R&D expenditures and to maintain the national R&D capacities, policymakers in many industrialised countries, including Austria, Denmark and Sweden, reacted immediately to the most recent crisis and increased the public R&D budgets (OECD, 2012b). In Germany, the

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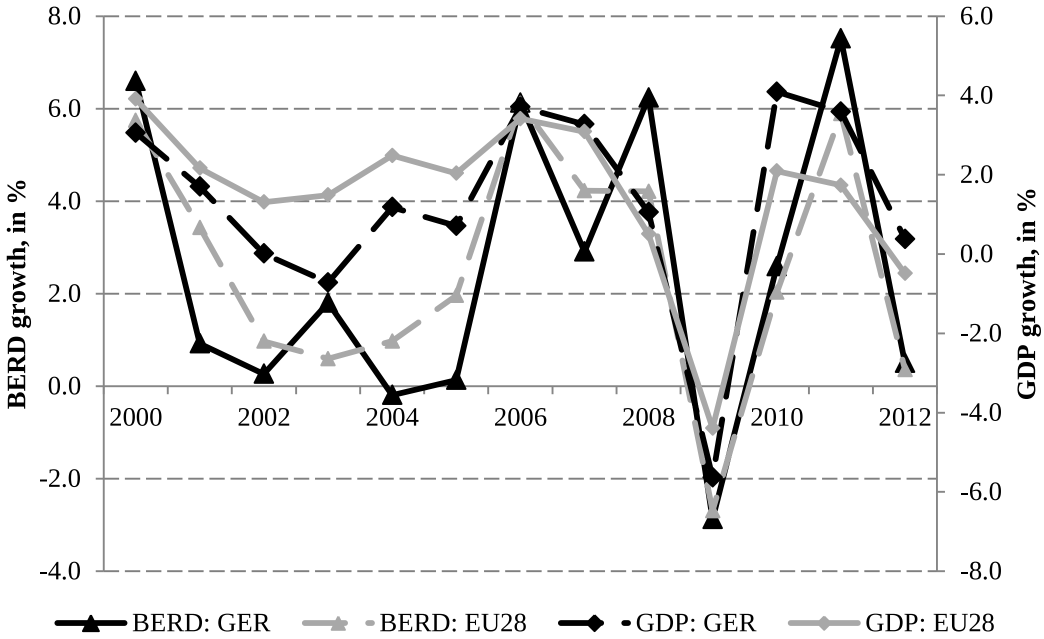
private sector reduced R&D expenditures by -2.9% (see Figure 2.1), whereas the German Federal Ministry for Education and Research (BMBF) reacted to the crisis by increasing its budget by 9% in 2009 as compared to 2008.

This chapter empirically examines the effects of the BMBF's public R&D subsidy program on firms' R&D investment during the most recent crisis. Our analysis is based on firm-level data of the Mannheim Innovation Panel (MIP) and on public R&D subsidy data provided by the BMBF. We focus on small and medium-sized enterprises (SMEs) because these firms are expected to be more vulnerable during an economic downturn as compared to large enterprises. Our sample covers the period of 2006-2010, with 2009 marking the peak of the crisis period in Germany (and the EU) as revealed in Figure 2.1.[3]

Our empirical strategy consists of several steps. We rely upon propensity score matching in order to assess whether R&D subsidies stimulate additional R&D investment over the sample period or not. The matching estimator accounts for the fact that subsidies are not randomly distributed among firms but that those firms self-select into the funding scheme. This procedure provides us with an estimate of the average effect of subsidies on the subsidised firms' R&D investment. In the next step, we compare the efficacy of the treatment of the crisis period to the pre-crisis (2006-2008) and post-crisis (2010) periods. In the final step, we test whether or not SMEs subsidised during the crisis were less promising innovators than SMEs that were subsidised before the crisis or whether or not the investment behaviour of subsidy recipients changed during the crisis. The former could be a consequence of an expanded subsidy program during the crisis that could have lowered the average "quality" of the pool of subsidy recipients.

Figure 2.1: Annual real GDP growth and real business enterprise expenditure on R&D (BERD) growth in Germany and EU28 between 2000 and 2012, in %



Source: OECD and OECD (2013a); authors' own calculation.

Note: Real GDP and BERD growth rates are calculated based on GDP and BERD at constant 2005 USD.

Our results show evidence that R&D subsidies lead to an additionality effect for the overall period. Only for the crisis year, we find evidence for a crowding out effect from which SMEs

[3] Germany was already severely affected by the crisis in the last quarter of 2008 reaching the peak in 2009. However, this does not show up in the aggregate annual data. Therefore, we refer to 2009 as the crisis year in the remainder of the chapter.

have already started to recover again in the post-crisis year 2010. The crowding out effect of the crisis year can be indicative of reluctant R&D investment behaviour of the subsidy recipients or of the counter-cyclical innovation policy that may has changed the average "quality" of the pool of subsidy recipients during the crisis. Further empirical tests suggest that the crowding out effect is caused by SMEs' reluctance to invest in R&D during a crisis period. We do not find support for the potential reason that the crowding out effect is related to a lower average "quality" of subsidised firms in the crisis and post-crisis years due to the expanded subsidy program. Although our main finding is that the average additionality effect is negative for the crisis year 2009, the counter-cyclical innovation policy is likely to have had a stabilising effect on the economy. It may have helped SMEs to keep their R&D personnel and to maintain national innovation capacities.[4]

The remainder of the chapter is organised as follows. The next section surveys related literature. Section 2.3 discusses our empirical strategy. The data set is described in Section 2.4. The results are discussed in Section 2.5. The last section concludes.

2.2 Literature review

2.2.1 The rationale for public R&D subsidies

The economic rationale for R&D subsidies to the private sector is that the level of privately financed R&D in the economy is lower than socially desirable. This is because R&D has the characteristics of a public good as it generates positive external effects, which cannot be internalised by the innovating firms (Arrow, 1962). In the absence of public subsidies, projects that would generate positive benefits for society but do not cover the private costs would not be carried out. This type of market failure is the main reason for governments to subsidise private R&D projects. Public funding reduces the price for private investors so that the otherwise too expensive innovation projects are carried out. The policymakers' objective is twofold with respect to R&D subsidies. On the one hand, the aim is to maintain national innovation capabilities, i.e. the national R&D and employment level. This is particularly the case for recession periods, where subsidies to the private sector are typically preferred over public procurement because of the potential of additionality effects. On the other hand, the government's interest is to generate more innovation outcome. Public subsidies can help the economy to recover from a crisis by fostering the creation of new innovations leading to economic growth.

However, the positive effect of R&D subsidies on firms' R&D activities cannot be taken for granted. In practice, firms always have an incentive to apply for public R&D support due to relatively low application costs. This holds even in the cases the expected net return of the project is positive or the R&D projects could be conducted with own financial means. Once a firm's application was successful, firms can use the public grant to replace private with public investment. This is called a "crowding out" effect (see e.g. David et al., 2000). If the majority of firms acted this way, public R&D subsidies would lead the economy to a lower growth path in the long-term. The likelihood of crowding out may be particularly high during recession periods when firms face declining sales markets and deteriorating financial markets hampering the financing of R&D projects. Firms may use the additional risk-free money to service short-term debt or to maintain their production capacities.

A vast empirical literature has investigated the question whether R&D subsidy programs lead to a crowding out effect or stimulate R&D activities in the private sector. The majority of the

[4] According to the German R&D statistics, R&D personnel are the largest cost unit in a firm's R&D process (Stifterverband, 2013).

studies find that R&D subsidies lead to an additionality effect (see Zúñiga-Vincente et al., 2014, for a recent survey). The early literature up to the year 2000 – as surveyed by David et al. (2000) and Klette et al. (2000) – is criticised for disregarding a potential selection bias of firms into R&D subsidy programs. On the one hand, firms with larger R&D capacity are more likely to apply for R&D subsidies. On the other hand, these firms may be more likely to receive the public funds in case the government targets to maximise the returns to the subsidy program. Hence, a simple comparison of subsidised and non-subsidised firms would lead to biased results. The more recent literature with focus on the firm level as surveyed by Zúñiga-Vincente et al. (2014) takes the selection problem into account. Prominent methods that have been used to account for sample selection are matching methods (e.g. Czarnitzki and Fier, 2002; Almus and Czarnitzki, 2003; Czarnitzki et al., 2007, for heterogeneous treatments), instrumental variables methods (e.g. Wallsten, 2000), and selection models (e.g. Busom, 2000; Hussinger, 2008).[5] The majority of the studies accounting for selection issues find a positive effect of the subsidy on the subsidised firms' R&D expenditures as well.[6]

Prior literature with a focus on Germany shows only positive average effects of R&D subsidies. For the direct project subsidy program of the BMBF, which is also subject to our study, Czarnitzki and Fier (2002), Almus and Czarnitzki (2003), Czarnitzki and Hussinger (2004), Czarnitzki et al. (2007), Hussinger (2008), and Aerts and Schmidt (2008) report that the subsidy leads on average to additional R&D expenditures.

2.2.2 Private innovation expenditures during economic downturns

The economic literature has developed different views on the impact of an economic downturn on innovation activities. One line of research advocates counter-cyclical behaviour of R&D investment. In times of an economic downturn, profitability declines encourage firms to seek for measures to improve productivity. At the same time, opportunity costs of reallocating productive assets from manufacturing to R&D are relatively low because of a limited demand for goods and services (Stiglitz, 1993; Aghion and Saint-Paul, 1998).

The contrary perspective suggests that innovation behaviour is pro-cyclical. Innovation strongly depends on demand so that there is no incentive to introduce new products into the market if demand is low (Schmookler, 1966, Shleifer, 1986). Further, R&D is often financed by a firm's free cash flow that depends on the firm's current profit so that financial constraints during an economic downturn reduce investment in R&D (Hall 1992; Himmelberg and Petersen 1994; Harhoff, 1998; Rafferty and Funk, 2008).

2.2.3 Private innovation expenditures during the most recent economic crisis

The most recent crisis caused an overall decline of innovation activities across OECD countries, whereby different countries have been affected to a different degree (OECD, 2012b; Makkonen, 2013). Some OECD economies show significantly reduced R&D figures for the private sector during the crisis, among them are Canada, the Czech Republic and the Netherlands. Others show slightly decreased R&D expenditures during the crisis such as Austria, Belgium, and Germany. In Germany, "business enterprise expenditure on R&D" (BERD) decreased by -2.9 % in 2009 compared to 2008. A possible reason is that the federal

[5] Gonzales et al. (2005) and Takalo et al. (2008) present structural models to assess the effect of subsidies on the subsidised firms.

[6] Exceptions are Busom (2000), who finds a partial crowding out effect for Spain, and Wallsten (2000), who reports a substitutive effect of subsidies for the U.S. SBIR program. Gelabert et al. (2009) find differences in the efficacy of public subsidies depending on the level of appropriation in the firm's industry.

government adopted a counter-cyclical policy and increased its government spending ("*government budget appropriations or outlays for R&D"*, GBAORD) by 9 % between 2007 and 2009 (OECD, 2012b; Makkonen, 2013). Other economies including China, Estonia and Hungary show an upward trend of private R&D expenditures throughout the crisis (OECD, 2012b).

Heterogeneous responses to the crisis have also been observed at the firm level. For instance, estimations using UK innovation surveys show that the recent crisis has severely reduced the firms' willingness to conduct innovation activities. However, some firms including fast-growing new firms and highly innovative firms even increased their innovation investment throughout the crisis (Archibugi et al., 2013a). In addition, by using data from the European-wide Innobarometer Archibugi et al. (2013b) find that, for instance, smaller firms and collaborating firms were "swimming against the stream". This means that those types of European firms increased their innovation investment during the recent crisis period. With regards to Latin American countries, Paunov (2012) shows that many firms stopped ongoing innovation projects during the crisis. With focus on public funding, Paunov (2012) finds that the likelihood to stop projects correlates negatively with the receipt of public funding and concludes that public funding schemes are an important means to foster counter-cyclical investment behaviour. However, she does not take a potential selection bias of firms' public funding receipts into account.

Based on a survey, Kulicke et al. (2010) conclude that the majority of firms in Germany have been forced to stop or postpone their R&D projects during the crisis as well. Rammer (2011) shows that the innovation expenditures of German firms in the research-intensive manufacturing sector decreased by -9.5%. They decreased by -16.7% in other manufacturing industries (see Rammer, 2011, Table 2).[7] In particular, small firms were affected. About 20,000 of them stopped their innovation activities (Rammer, 2011).

A recent study investigates the macroeconomic effects of R&D subsidies granted by the "Central Innovation Program for SMEs" (ZIM) program that was launched in 2008 in Germany (Brautzsch et al., 2015). Brautzsch et al. (2015) conclude that the ZIM program stabilised production, value added and employment during the crisis which prevented a GDP decline of about 0.5%. Our study complements their findings by providing microeconomic evidence for the effects of R&D subsidies on SMEs' R&D investment during the crisis. In contrast to Brautzsch et al. (2015), our data also allow us to compare the crisis behaviour of SMEs with the pre-crisis period.

2.3 Empirical strategy

Our empirical approach has three different parts. The first part evaluates the efficacy of R&D subsidies for the entire sample period. The second part compares the effect of subsidies in the crisis year to pre- and post-crisis years. In the last part of the analysis, we investigate possible reasons for a different effect of subsidies in crisis and non-crisis years.

2.3.1 Efficacy of R&D subsidies

The aim of our policy evaluation is to assess the average effect of the public subsidy on the firms' R&D spending of the subsidised SMEs. As a simple comparison between treated (subsidised) and non-treated (non-subsidised) SMEs is likely to be biased due to selection problems,[8] our empirical approach aims at investigating the potential average amount firms

[7] Rammer's (2011) calculations are based on the same survey that we use for the empirical analysis.

[8] For a detailed discussion of the selection problem see e.g. Blundell and Costa Dias (2008).

under the treated condition would have spent on R&D expenditures if they had not received the subsidy. That is, we need to estimate the counterfactual situation. This average treatment effect on the treated (ATT) is defined as follows:

$$ATT = E(Y_1 - Y_0|S = 1) = E(Y_1|S = 1) - E(Y_0|S = 1) \tag{2.1}$$

where Y_1 is the R&D spending of the SMEs having received the treatment (i.e., the subsidy) and Y_0 is the R&D expenditures of SMEs that did not receive a subsidy. The variable S depicts the actual treatment status. This equation indicates a missing data problem: While we can observe $(Y_1|S = 1)$, i.e. the R&D spending of a subsidised firm, we cannot observe what the subsidised firm would have spent on R&D without the subsidy $(Y_0|S = 1)$.

The construction of a valid proxy variable for the counterfactual situation is the main issue in empirical policy program evaluation. Econometric techniques serving to overcome this problem comprise difference-in-difference (DID) estimations, control function approaches (selection models), instrumental variables (IV) estimations, and matching techniques. Due to highly unbalanced panel data and a lack of reliable instruments and exclusion restrictions, we choose a matching approach. The intuition behind the matching estimator is to proxy the counterfactual situation, i.e. the R&D investment of a treated firm in the absence of the treatment, by the R&D investment of the most similar non-treated observation. Functional form assumptions and distributional assumptions about the error terms are not required. The disadvantage of the matching approach is that it only accounts for selection based on observable firm characteristics. Prior studies focussing on the efficacy of our subsidy program in Germany, however, show comparable results independent of the method that was employed (see e.g. Almus and Czarnitzki, 2003, Czarnitzki et al., 2007, Hussinger, 2008).

We apply a nearest neighbour propensity score matching. This means that we match each subsidy recipient with the single most similar SME in the control group of the non-subsidised SMEs. The pairs are chosen based on the similarity in the estimated probability of receiving a subsidy, i.e. the propensity score. Matching on the propensity score avoids a "curse of dimensionality" because all required information is bundled in the propensity score, which is then used as the single matching argument (Rosenbaum and Rubin, 1983). In addition, we require that the selected control observation is observed in the same year as the treated observation. This is crucial for our analysis because we are interested in comparing treatment effects across years. We further demand that the control observations are located within the same geographical area in Germany by distinguishing between East and West German firms. We apply this distinction because the funding likelihood as well as the infrastructure for innovation significantly differs between these two regions.

The matching estimator's main disadvantage is its reliance on the conditional independence assumption (CIA). This means, the assignment to treatment is required to be independent of the outcomes, in our case the R&D investment, conditional on a set of observable characteristics (Rubin, 1977). The CIA will be satisfied if all information affecting the treatment assignment and the outcome is included in the set of observable characteristics. If this is the case, the observed non-treated outcome $E(Y_0|S = 0)$ will be a valid proxy for the unobservable counterfactual outcome $E(Y_0|S = 1)$. Unfortunately, it is not possible to formally test the CIA. However, we are confident that our rich set of control variables suffices.[9] A further requirement of the matching method is that there has to be sufficient overlap between the treated and the control group in terms of their propensity to receive a

[9] A similar set of control variables has been used in a variety of studies that evaluate the effects of R&D subsidies based on similar data sets employing a matching approach (e.g. Czarnitzki and Fier, 2002; Almus and Czarnitzki, 2003; Czarnitzki et al., 2007; Czarnitzki and Lopes Bento, 2013).

public subsidy (common support). In order to guarantee common support, we calculate the minimum and the maximum of the propensity scores of the potential control group, and delete observations on treated firms with probabilities larger than the maximum and smaller than the minimum in the potential control group. If the CIA and the common support are fulfilled, the ATT will be identified and consistently estimated by the following equation:[10,11]

$$ATT = (Y_1|S = 1) - E(Y_0|S = 0) \qquad (2.2)$$

2.3.2 Efficacy of R&D subsidies in crisis and non-crisis years

After the identification of the ATT, we investigate whether the effect of subsidies differs in the crisis and non-crisis years by running an OLS regression of the ATT on a set of time dummies d_t.

$$\widehat{ATT_t} = \beta_0 + \sum_{n=2007}^{2010} \beta_n d_{n,t} + u_t \qquad (2.3)$$

There are two different scenarios possible. First, one can expect that the subsidies are more effective in the crisis year because firms may face more severe financial constraints so that the subsidy increases R&D investment substantially as compared to the counterfactual situation. Second, a lower treatment effect can occur in the crisis year if firms match the public funds with less private investments than they would have made in non-crisis years or replace private investments by public funds.

2.3.3 Explanations for possible different effects of R&D subsidies in crisis and non-crisis years

In the final part of the analysis, we investigate possible explanations for the potential differences of the efficacy of R&D subsidies in crisis and non-crisis years. Such differences can be motivated by (a) an altered funding policy in crisis times or (b) a change of behaviour of grant recipients in crisis times:

(a) During the most recent crisis, direct project funding has been increased in terms of granted amounts per project and number of projects funded. This could have reduced the ATT because if more projects were funded the average “quality” of the recipients was likely to be lower than in non-crisis years.
(b) Subsidy recipients may have faced tighter budget constraints during the crisis. In response, they have probably invested less into the subsidised R&D projects than they would have invested in non-crisis years.

In order to analyse whether the change in innovation policy affected the effect of R&D subsidies during the crisis, we compare first-time subsidised firms in crisis and non-crisis years. If a lower subsidy effect were caused by a lower average “quality” of funded firms

[10] The details of our matching procedure (matching protocol) are provided upon request. Very similar matching protocols can be found e.g. in Czarnitzki and Hussinger (2004), Aerts and Schmidt (2008) and Czarnitzki and Lopes Bento (2013).

[11] A similar matching approach has been used among others by Almus and Czarnitzki (2003), Czarnitzki and Hussinger (2004), Görg and Strobl (2007), Gonzales and Pazo (2008), Czarnitzki and Lopes Bento (2013) and Hottenrott et al. (2014).

during the crisis years, we should find a significant difference between these groups of firms in terms of success predictors like firm size or patent stock.

In order to investigate whether or not firms changed their R&D investment behaviour, we repeat the analysis described in Section 2.3.2 for the subsample of SMEs that received subsidies before, during and after the crisis. If we found that these companies reduced their R&D investment we could conclude that a potential decreased efficacy of R&D subsidies was caused by firms' reluctance to invest in R&D projects during the crisis rather than by the counter-cyclical innovation policy.

2.4 Data, variables and descriptive statistics

2.4.1 Data sources

For our empirical analysis of a potential additionality effect of R&D subsidies, we construct a data base that includes firm level information and the firms' subsidy records. The firm-level data are provided by the Mannheim Innovation Panel (MIP), which is an annual survey conducted by the Centre for European Economic Research (ZEW) on behalf of the German Federal Ministry for Education and Research (BMBF) since 1993. The MIP is the German contribution to the European Commission's Community Innovation Survey (CIS) and is based on the methodology proposed in the Oslo Manual for collecting innovation data (OECD and Eurostat, 2005).[12]

Information on the Federal Government's project funding is taken from BMBF's PROFI data base, which is available to us from 1992 onwards. It contains information on all non-military R&D projects funded by the BMBF. The BMBF program is the most encompassing source of public R&D funds for the business sector in Germany and accounts for a large part of the total R&D subsidies available to the business sector. The direct project funding program is open to all firms located in Germany. The official application form requires detailed information on the firm and its planned R&D projects. There is a peer review process according to which grants are assigned as "matching grants" to the selected projects, which means that applicants themselves have to contribute at least 50% to the subsidised projects. The government sponsors at most 50% as is prescribed in the funding guidelines of the European Commission (EC, 1996) and in German regulations (BMBF and BMWi, 2001).

We use three additional data sources for our analyses. First, data from the European Patent Office (EPO) provides us with firms' patent applications since 1979. This allows us to calculate each firm's patent stock. Second, data drawn from Germany's largest credit rating agency Creditreform allow us to use information on firm age and firms' credit rating. The latter indicates the firms' financial fitness. Third, the Federal Statistical Office of Germany (Destatis) provides us with a measure for the business cycle. We constructed the annual change of industry-level sales growth based on 4-digit industry-level data (NACE 2.0).[13]

The final sample covers the years 2006 to 2010 in order to cover the pre-crisis period (2006-2008), the crisis year (2009) and the post-crisis period (2010). The choice of the time frame for our study is motivated by the fact that we want to exclude the recession 2002/2003 and the following recovering period. In contrast to the most recent economic crisis, the recession 2002/2003 was expected by German firms (Rammer et al., 2003) so that we would not be able to identify causal effects. With respect to the recent economic crisis, Rammer (2011) shows that in the years 2006 to 2008 the actual innovation expenditures of German firms of all size

[12] For further details see Aschhoff et al. (2013) and Peters and Rammer (2013).

[13] For a few industries we had to use the 2-/3-digit level.

classes were almost equal to the innovation expenditures planned in the previous year. Only in the crisis year 2009, a large gap between planned and actual innovation expenditures arises (see Figure 1 in Rammer, 2011).

We restrict our sample to firms with less than 250 employees, as almost each European firm is a SME and they are most sensitive to the business cycle (OECD, 2009). Our sample includes manufacturing as well as business related service sectors. The final sample includes 10,527 firm-year observations out of which 1,016 received an R&D subsidy from the BMBF over the observed period.

2.4.2 Variables

2.4.2.1 Treatment variable

We measure treatment with a binary indicator that takes on the value 1 in the case a firm was subsidised by the BMBF in the respective year. The indicator takes on the value 0 if a firm did not receive any R&D subsidy at all in the respective year, neither from the EU nor from the Federal Government nor from other public sources. Hence, our control group solely includes non-subsidised firms, which allows us to rule out side effects from other subsidy programs. Table 2.1 shows the distribution of subsidised firms and unsubsidised firms in our sample over time. It becomes evident that the number of subsidised firms has increased during and after the crisis. The number of newly funded firms is still small in the crisis year 2009, but increases significantly in 2010.

Table 2.1: Overview of subsidised and non-subsidised firms over time

	2006	2007	2008	2009	2010	Total
Not subsidised	1,579	1,715	2,358	1,925	1,934	9,511
Subsidised	191	176	153	194	302	1,016
First-time subsidised after 2008	6	5	8	15	93	127

Source: PROFI data base and MIP; authors' own calculation.

Note: Due to the panel structure of our data set, observations of firms subsidised for the first time after 2008 can also appear in 2006, 2007 and 2008.

2.4.2.2 Outcome variables

We test potential additionality effects for six outcome variables in order to show robustness of the results with regards to different definitions of the dependent variable. *RD* depicts a firm's total R&D expenditures, which is measured in million EUR. *PRIVRD* is defined as the private R&D investment, i.e. *RD* minus the subsidy amount received. As these variables are distributed askew, we employ *RDINT* (*RD* over sales) as well as *PRIVRDINT* (*PRIVRD* over sales) in addition. Furthermore, we define *RDEMP* (*RD* over number of employees) and *PRIVRDEMP* (*PRIVRD* over number of employees) as alternative measures for the intensity indicators.

2.4.2.3 Control variables

Our control variables include firm size as measured by the log of the number of full-time employees, *Lemp*. We expect R&D expenditures to correlate with firm size. In this sense, larger firms were more likely to apply for subsidies and to receive a grant if the government wanted to maximise the likelihood of a positive outcome of the funded project by choosing firms with superior innovation capacities. The logarithmic specification is chosen because of the skewness of the firm size distribution.

If a firm is part of an enterprise group, this membership could improve the access to innovation capacity and also to information on governmental programs. This may result in a higher likelihood to apply for a subsidy. Further, governmental evaluators could be prone to subsidise firms that belong to a network of firms, being aware of potential knowledge spillovers within the enterprise group due to the subsidised project. We control for firms belonging to a firm group with a binary variable, *Group*. Firm groups having a foreign headquarter, *Foreign*, were, in contrast, less likely to receive funding in case the German policymakers primarily intended to strengthen the development of the German economy. The binary variable *East* indicates whether a firm is located in Eastern Germany or in the Western part of the country. East German firms could be more likely to receive a subsidy as this region is still in a catch-up process as compared with the Western German regions. The log of firm age, *Lage*, covers potential firm age effects. Firms competing in foreign markets are supposed to be more innovative than others (Arnold and Hussinger, 2005). Therefore, we also expect export-oriented firms to apply more frequently for public R&D support. Our binary dummy *Export* indicates whether a firm has export sales or not. Furthermore, we account for a firm's innovation potential by past innovation success in terms of the firm's patent stock. To construct the patent stock, we use patent applications from 1979 onwards that have been filed at the EPO. The patent stock in year t is calculated as a depreciated sum of all these patent applications until year t-1 plus the (non-depreciated) patent applications in year t. The depreciation rate is set to 15%, as is common in the literature (see e.g. Hall, 1990; Griliches and Mairesse, 1984). Due to collinearity concerns with firm size, the patent stock is normalised by the number of employees, *Patemp*. To account for potential financial restrictions, particularly during the crisis period, we include Creditreform's credit rating index, *Credit*.[14] This is an index representing a firm's solvency. The index ranges from 100 to 600. The larger the index value, the lower is the credit rating and the ability to attract debt capital. Firms that have more problems to attract external finance may be more likely to apply for subsidies.

We also control for the receipt of past subsidies. Firms that received subsidies in the past have a high chance that a new application will be evaluated positively (Hussinger, 2008; Aschhoff, 2010). We use a dummy for past subsidy receipt with a four year lag to account for the fact that the average subsidised R&D project lasts for about three years, *Sub_t-4*. Another characteristic to be considered is the business climate of the firm's industry sector. SMEs usually participate only in one or a few product markets. In case of economic downturns, these firms may not have the opportunity to compensate a serious decrease of demand in one of their few markets. We control for the firms' business environment by including an industry-specific sales growth rate, *Sales_growth*. To avoid potential endogeneity, we lag all time-variant explanatory variables and consider *Group, Foreign, East* as time-invariant and *Sales_growth* and *Lage* as exogenous to the firm. In addition, we also include a set of interaction terms that measures potential period-specific effects on the probability of subsidy receipt. For this reason, we multiply each covariate with a dummy variable that takes on the value one if the firm is observed in the (post-) crisis period, i.e. in 2009 or 2010, and it is zero otherwise. We label those interaction terms as "*_period*" for the respective variable.

2.4.3 Descriptive statistics

Table 2.2 shows descriptive statistics that compare the variables' mean values and standard deviations of non-subsidised and subsidised firms. Significant t-tests indicate systematic differences between the mean values of the variables for subsidised and non-subsidised firms.

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[14] We also employ a missing value correction (see Allison, 2001). The missing values of *Credit* are set to zero. An additional binary dummy, *Credit_mvd* that takes on the value 1 if Credit equals zero is included in the estimations.

Table 2.2: Descriptive statistics for the whole sample, separated by subsidy status

	Unsubsidised firms N = 9,511		Subsidised firms N = 1,016		t-test
	Mean	Std.dev.	Mean	Std.dev.	
Covariates:					
Sub_t-4	0.006	0.079	0.338	0.473	***
Patemp	0.001	0.015	0.027	0.085	***
Lemp	3.165	1.093	3.460	1.091	***
Foreign	0.047	0.213	0.068	0.252	**
Export	0.404	0.491	0.802	0.399	***
Group	0.213	0.409	0.247	0.432	**
Lage	3.096	0.858	2.679	0.728	***
East	0.337	0.473	0.410	0.492	***
Sales_growth	2.459	13.208	4.068	13.947	***
Credit	225.487	65.334	226.054	52.911	
Credit_mvd	0.035	0.185	0.023	0.149	**
Controlling for period differences:					
Sub_t-4_period	0.003	0.054	0.148	0.355	***
Patemp_period	0.000	0.005	0.014	0.066	***
Lemp_period	1.263	1.680	1.651	1.851	***
Foreign_period	0.017	0.127	0.029	0.167	**
Export_period	0.156	0.363	0.390	0.488	***
Group_period	0.080	0.271	0.118	0.323	***
Lage_period	1.275	1.632	1.305	1.432	
East_period	0.138	0.345	0.172	0.378	***
Sales_growth_period	-0.635	10.543	0.919	12.443	***
Credit_period	91.563	117.935	111.111	119.564	***
Credit_mvd_period	0.014	0.119	0.010	0.099	
Outcome variables:					
RD	0.036	0.310	0.705	2.586	***
PRIVRD	0.036	0.310	0.577	2.310	***
RDINT	0.005	0.035	0.150	0.220	***
PRIVRDINT	0.005	0.035	0.098	0.184	***
RDEMP	0.001	0.004	0.013	0.023	***
PRIVRDEMP	0.001	0.004	0.009	0.020	***

Source: PROFI data base and MIP; authors' own calculation.

Note: * p<0.1; ** p<0.05; *** p<0.01; for reasons of clarity, we dropped the information on industry dummies and their period differences from this table.

For instance, subsidised firms score higher on each R&D input measure. They have more patents per employee and more employees in general. In addition, they are more likely to be exporters. Furthermore, subsidised SMEs are younger and are more frequently located in Eastern Germany. In contrast, subsidised SMEs, on average, are related to higher sales growth rates on the industry level. This means, the focal industries the subsidy recipients have been operating in have experienced a larger growth to the focal industries of the non-subsidised firms. This suggests that SMEs will be more likely to apply for and receive a subsidy if their focal industry experiences an economic upturn period. Furthermore, the credit rating between non-subsidised and subsidised firms does not differ significantly. Both firm groups reveal an average share that ranges around 225. A value of this magnitude indicates a firm to have a good financial standing.[15] The period differences refer to the variables' mean values of the firms that were observed in 2009 and 2010 (see Section 2.4.2.3). The relationship between the

[15] Similar results for the exogenous variables appear if comparing them between the pre-crisis and the (post-) crisis periods. However, almost no significant differences are found for the outcome variables (see Table 2.A.1).

subsidised and the unsubsidised firms observed in 2009 or 2010 is similar to the overall observations just presented. For instance, subsidy recipients that were observed in at least one of the two years have a larger patent portfolio, have more employees and are more export-oriented than their unsubsidised counterparts.

2.5 Empirical results

2.5.1 Funding propensity

As described in Section 2.3.1, we employ a matching estimator as a first step to identify the causal effect of the subsidy treatment on R&D investment. Therefore, we have to find non-subsidised observations with the most similar characteristics to the subsidised observations.

Table 2.3: Probit estimation of subsidy receipt

	Coefficients	Std.err.
Sub_t-4	**2.187*** **	(0.118)
Patemp	**4.568*** **	(0.700)
Lemp	**0.149*** **	(0.032)
Foreign	0.050	(0.127)
Export	**0.775*** **	(0.075)
Group	**-0.243*** **	(0.084)
Lage	**-0.273*** **	(0.042)
East	**0.245*** **	(0.065)
Sales_growth	-0.003	(0.004)
Credit	**-0.002** **	(0.001)
Credit_mvd	**-0.686*** **	(0.243)
Industries:		
Mining	**-1.130*** **	(0.294)
Low-tech manuf.	**-0.984*** **	(0.098)
High-tech manuf.	**-0.423*** **	(0.099)
Energy/water/recycl.	**-1.012*** **	(0.163)
Wholesale	**-1.909*** **	(0.356)
Transportation	**-1.389*** **	(0.202)
ICT	-0.171	(0.117)
Consulting/advert.	**-0.800*** **	(0.180)
Years:		
2007	-0.069	(0.074)
2008	**-0.293*** **	(0.074)
2009	0.117	(0.398)
2010	0.328	(0.398)
Constant	**-0.645** **	(0.260)
Observations	10,527	
Log-likelihood	-1,968	
McFadden's R2	0.411	
Time dummies (chi2):	**24.26*** **	
Industry dummies (chi2):	**183.6*** **	
Period interactions (chi2):	**77.26*** **	

Source: PROFI data base and MIP; authors' own calculation.

Note: * p<0.1; ** p<0.05; *** p<0.01; see Table 2.A.2 for the full table.

We determine the so called nearest neighbours based on the propensity score, i.e. the likelihood of receiving a subsidy. In order to get an estimate for the propensity score we estimate a Probit model for the receipt of public subsidies. We allow that our control variables have a different impact on the receipt of subsidies in the pre-crisis period and thereafter by including interaction terms of all control variables with a year dummy for 2009 and 2010. Table 2.3 shows the results. According to this table, most of the estimates show the expected effects. The past subsidy indicator, *Sub_t-4*, is positively related to a subsidy receipt in year t as is a higher patent stock and a higher level on employees. Firms that export as well as Eastern German firms also have a significantly positive effect on the probability of subsidy receipt. We also expected the firm group indicator to be positively associated with a firm's subsidy status. However, its estimate is negative and strongly significant. Furthermore, as almost all estimates have a strongly significant effect on the dependent variable, it seems that we have controlled for the important indicators to explain a firm's subsidy receipt.

2.5.2 Average treatment effect on the treated

In a second step, we determine "twin observations" of non-subsidised SMEs for each subsidised SME observation.

Table 2.4: Matching results

	Unsubsidised N = 998	Subsidised N = 998	t-test	p-values
	Mean	Mean		
Covariates:				
Sub_t-4	0.347	0.333		0.720
Patemp	0.013	0.019		0.115
Lemp	3.539	3.461		0.416
Foreign	0.081	0.067		0.528
Export	0.804	0.802		0.951
Group	0.302	0.245		0.134
Lage	2.699	2.681		0.739
East	0.414	0.414		1.000
Sales_growth	4.117	4.089		0.982
Credit	228.667	226.270		0.649
Credit_mvd	0.027	0.022		0.704
Controlling for period differences :				
Sub_t-4_period	0.152	0.141		0.708
Patemp_period	0.006	0.008		0.293
Lemp_period	1.755	1.626		0.428
Foreign_period	0.041	0.027		0.379
Export_period	0.390	0.384		0.881
Group_period	0.139	0.114		0.374
Lage_period	1.291	1.286		0.963
East_period	0.171	0.171		1.000
Sales_growth_period	0.973	0.899		0.949
Credit_period	105.868	109.789		0.684
Credit_mvd_period	0.014	0.009		0.595
Outcome variables:				
RD	0.306	0.676	***	0.001
PRIVRD	0.306	0.548	**	0.021
RDINT	0.029	0.146	***	0.000
PRIVRDINT	0.029	0.095	***	0.000
RDEMP	0.004	0.012	***	0.000
PRIVRDEMP	0.004	0.009	***	0.000

Source: PROFI data base and MIP; authors' own calculation.
Note: * p<0.1; ** p<0.05; *** p<0.01; for reasons of clarity, we dropped the industry dummies and their period differences from this table but each difference of the mean values is not significantly different from zero.

As matching criteria, we used the propensity score and the additional two matching arguments – location in Eastern Germany and year of observation. Due to the common support criterion we have to drop two observations for which we cannot determine appropriate control observations. Table 2.4 shows the mean values for treated and control observations after the matching. There no longer exist significant differences between the treated and the non-treated observations with regards to the control variables indicating that our matching specification is valid.[16] Significant differences in the mean values of the outcome variables persist and can be given a causal interpretation now after the matching.

The subsidised firms show a higher R&D activity independent of the definition of the outcome variable. Hence, we find an overall positive ATT. This signals that firms increased their R&D spending due to the subsidy across the observed periods. We do not find any support for a crowding out. The ATT equals 0.370 (0.242) million EUR in terms of R&D (private R&D) expenditures. The ATT in terms of R&D (private R&D) over sales corresponds to 11.7% (6.6%) points. For R&D intensity as defined by R&D over employment the ATT amounts to 0.008 (0.005) for R&D (private R&D).

2.5.3 Average treatment effects in the course of time

In this section, we investigate potential changes of the average treatment effect on the treated over time. Table 2.5 presents the results of OLS regressions of the ATT on a set of year dummies. This specification's constant represents the ATT of the year 2006, our benchmark year. The estimated coefficients shown in this table mean that the ATTs are positive and significant, on average, with one exception. With regards to the R&D expenditures and private R&D expenditures, the ATT in 2009 is significantly lower and even negative (0.763-1.006 < 0; 0.599-0.942 < 0) as compared with the base value of 2006. This indicates a crowding out effect. In 2010, the effect is still lower but larger than zero (0.763-0.522 > 0; 0.599-0.464 > 0), indicating a smaller, yet positive additionality (treatment) effect. With regards to the R&D intensity variables we find a smaller additionality effect in the crisis year 2009 and no significant change for the post-crisis year.

Table 2.5: OLS results of the average treatment effects on time dummies

	RD	PRIVRD	RDINT	PRIVRDINT	RDEMP	PRIVRDEMP
2007	-0.341	-0.329	0.010	-0.000	-0.000	-0.000
	(0.315)	(0.268)	(0.025)	(0.022)	(0.003)	(0.002)
2008	0.053	0.088	-0.005	-0.004	0.002	0.002
	(0.440)	(0.397)	(0.027)	(0.025)	(0.003)	(0.003)
2009	**-1.006*** **	**-0.942*** **	**-0.056** **	**-0.055*** **	**-0.006** **	**-0.006** **
	(0.330)	(0.295)	(0.023)	(0.020)	(0.003)	(0.002)
2010	**-0.522***	**-0.464***	-0.030	-0.033	-0.003	-0.003
	(0.295)	(0.254)	(0.023)	(0.020)	(0.002)	(0.002)
Constant	**0.763*** **	**0.599** **	**0.135*** **	**0.087*** **	**0.010*** **	**0.007*** **
	(0.285)	(0.245)	(0.019)	(0.017)	(0.002)	(0.002)
Observations	998	998	998	998	998	998
R2	0.018	0.019	0.010	0.012	0.013	0.014

Source: PROFI data base and MIP; authors' own calculation.

Note: * p<0.1; ** p<0.05; *** p<0.01; robust standard errors in parentheses; the base year (constant) is 2006.

Table 2.A.3 in the Appendix shows a robustness check. We present results from pooled OLS regressions including interaction terms for the subsidy dummy and the year dummies. In

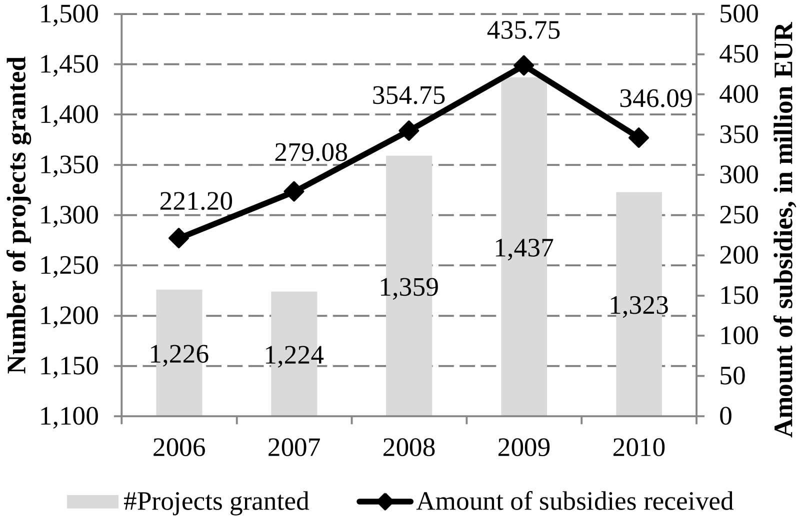
[16] This also holds for the controlling of the period differences. This means, the subsidised firms that were observed in 2009 or 2010 are not significantly different anymore in terms of the covariates as compared to their unsubsidised counterparts.

general, OLS models do not account for selection of firms into public subsidy programs. Nevertheless, the results are in line with the findings above, which suggest that the subsidies were less effective in the crisis year and post crisis years.

2.5.4 Potential explanations for the lower ATT

As mentioned in Section 2.3.3, the significantly lower ATT could be due to a changed funding policy during the crisis or due to altered investment behaviour of the firms. Figure 2.2 depicts the allocation policy of the BMBF for SMEs over the observed period. In 2006, 1,226 projects were granted with an overall amount of about 221 million EUR. During the crisis, this amount corresponded to 435 million EUR for 1,437 granted projects. This shows that the BMBF increased the number of projects granted as well as the total amount in 2009. In 2010, pre-crisis levels are achieved. The peak of 2009 could imply that the BMBF subsidised SMEs of lower average “quality” than in the pre-crisis years extending the pool of funded firms.

Figure 2.2: Funding development for SMEs between 2006 and 2010



Source: PROFI data base and MIP; authors’ own calculation.

In order to provide a formal test for potential quality differences of subsidy recipients before and during the crisis, Table 2.6 presents a Probit regression of a binary variable for first-time funded firms on a set of covariates. The binary indicator takes on the value one if the firm has been subsidised by the BMBF for the first time before the crisis year 2009, it is zero in case the firm has been subsidised by the BMBF for the first time after the crisis has started, i.e. after the year 2008. The sample only includes firms that have received subsidies by the BMBF at some point in their lifetime (1992-2010). If a first-time subsidy recipient before and during the (post-) crisis periods differed in terms of success indicators, we would see significant differences in the estimated effects of the firm characteristics. However, the regression results do not disclose systematic differences between first-time subsidy recipients in both periods indicating that the “quality” of the subsidy recipients did not significantly differ. The only significant differences are found for some industry and time dummies. Therefore, we decline the notion that the crowding out effect during the crisis year 2009 and the lower additionally effect in 2010 were caused by systematic differences between subsidy recipients before the crisis and afterwards.[17]

[17] In addition, we compare firms that received subsidies before the crisis with firms that received subsidies after the crisis started in terms of other economic performance characteristics, like labour productivity and innovation sales, as was suggested by a reviewer. However, we do not find a significant difference there either. The results are presented in Table 2.A.4 in the Appendix.

Table 2.6: Probit estimation of first-time funded firms

	Coefficients	Std. err.
Patemp	0.473	(0.813)
Lemp	-0.053	(0.066)
Foreign	-0.260	(0.246)
Export	0.177	(0.160)
Group	0.233	(0.157)
Lage	-0.026	(0.082)
East	0.133	(0.120)
Sales_growth	-0.002	(0.005)
Credit	0.001	(0.002)
Credit_mvd	-0.343	(0.496)
Industries:		
Low-tech manuf.	**-0.421****	(0.214)
High-tech manuf.	**-0.467****	(0.193)
Energy/water/recycl.	**-1.162*****	(0.301)
Wholesale	**-1.217***	(0.652)
Transportation	-0.185	(0.433)
ICT	-0.352	(0.232)
Consulting/advert.	-0.450	(0.297)
Years:		
2007	0.083	(0.274)
2008	-0.168	(0.253)
2009	**-0.519****	(0.249)
2010	**-1.379*****	(0.201)
Constant	**2.213*****	(0.572)
Observations	1,175	
Log-likelihood	-320.3	
McFadden's R2	0.204	
Industry dummies (chi2):	**17.89****	
Time dummies (chi2):	**99.04*****	

Source: PROFI data base and MIP; authors' own calculation.

Note: * p<0.1; ** p<0.05; *** p<0.01.

An alternative explanation for the crowding out effect is that it is induced by firms' altered investment behaviour. Firms had to cope with the negative consequences of the economic crisis. They may have allocated the funds that they would have spent on R&D projects to business areas that they deemed more important during the crisis. According to Rammer (2011), firms that were most severely affected by the crisis have been R&D active firms. We test whether or not firms' changed their R&D investment behaviour during the crisis by focussing on the subsample of SMEs that received subsidies before and during the crisis. We repeat the regressions presented in Table 2.5. Table 2.7 shows those results. It appears that we find a crowding out effect for the crisis year 2009 and a smaller, but again positive treatment effect for the post-crisis year 2010 for R&D and private R&D investment. This is in line with the presumption that SMEs changed their investment behaviour during the crisis rather than the altered innovation policy causing the reduced treatment effect in 2009.

Table 2.7: OLS regressions of the average treatment effects on the time dummies – subsample of firms that received R&D subsidies before, during and after the crisis

	RD	PRIVRD	RDINT	PRIVRDINT	RDEMP	PRIVRDEMP
2007	-0.341	-0.329	0.010	-0.000	-0.000	-0.000
	(0.315)	(0.268)	(0.025)	(0.022)	(0.003)	(0.002)
2008	0.053	0.088	-0.005	-0.004	0.002	0.002
	(0.441)	(0.397)	(0.027)	(0.025)	(0.003)	(0.003)
2009	**-1.070*** **	**-1.008*** **	**-0.056** **	**-0.057*** **	**-0.006** **	**-0.006*** **
	(0.334)	(0.299)	(0.024)	(0.021)	(0.003)	(0.002)
2010	**-0.502***	**-0.467***	-0.028	-0.033	-0.003	-0.003
	(0.303)	(0.262)	(0.025)	(0.022)	(0.002)	(0.002)
Constant	**0.763*** **	**0.599** **	**0.135*** **	**0.087*** **	**0.010*** **	**0.007*** **
	(0.286)	(0.245)	(0.019)	(0.017)	(0.002)	(0.002)
Observations	896	896	896	896	896	896
R2	0.019	0.021	0.010	0.012	0.013	0.015

Source: PROFI data base and MIP; authors' own calculation.

Note: * p<0.1; ** p<0.05; *** p<0.01; robust standard errors in parentheses.

2.6 Conclusion

Our study examines the effects of R&D subsidies on German SMEs' R&D spending during the most recent economic crisis. We start by investigating the average treatment effect on the treated (ATT) of direct R&D subsidies in Germany during the period 2006-2010. Using propensity score nearest neighbour matching, we find an overall positive ATT for the observed period. Further results show that the ATT was negative in the crisis year 2009 indicating a crowding out effect. In the post-crisis year 2010, however, we find again evidence for a positive average treatment effect of R&D subsidies on the funded SMEs' R&D expenditures. Even though this effect is still significantly smaller than the ATT found for the whole period, it is a signal that German SMEs recovered after the crisis' peak year 2009.

In search for an explanation for the crowding out effect in 2009, we investigate two potential causes. We analyse whether the BMBF's counter-cyclical innovation policy during the crisis is responsible for the crowding out effect or whether or not different investment behaviour of subsidy recipients in the crisis year was the cause. For instance, the expansion of the subsidy program during the crisis could have decreased the average "quality" of the subsidy recipients as compared to the pre-crisis years. This, in turn, could have lowered the average success of the subsidy program. In order to provide a formal test, we compare first-time subsidy recipients before and during the crisis by using a Probit model. The results show that there are no systematic differences between these two groups of firms. This means that e.g. larger firms or firms with a higher patent stock were not more likely to become a first-time subsidy recipient during/after the crisis than before the crisis. In order to investigate whether or not SMEs' R&D investment behaviour has changed during the crisis, we focus on the subsample of firms that received subsidies before, during and after the crisis and find that these firms significantly reduced their R&D expenditures in 2009 as well. Hence, we conclude that the crowding out effect is likely not to be caused by the R&D subsidy program expansion in the crisis year but that it is due to firm behaviour. To cope with negative effects of the crisis, SMEs may have shifted funds during the crisis that they would have spent on R&D projects in non-crisis years, to other business divisions or areas. This may helped them to keep their stock of employees. Despite this negative treatment effect, the counter-cyclical innovation policy of the BMBF is likely to have had a stabilising effect for SMEs helping them to pay the wages of R&D workers and to start new projects. The crowding out effect lasted only for one year after which SMEs recovered from the first shock of the crisis and returned to their pre-crisis R&D investment behaviour. Therefore, the likelihood of negative long run effects for the economy is rather low.

One limitation of our study is that we can only focus on additionality effects of R&D subsidies on R&D input rather than on additionality effects in terms of R&D output, a second measure of high interest for policy makers.[18] Whereas it is feasible to focus on input additionalities of R&D funding as they occur in the immediate funding years, output effects are distributed over a period of years after the funding was received depending on the complexity of the project. This means that the output effects of pre-crisis funding are visible in the pre-crisis period as well as in the crisis and in post-crisis years. As we cannot link particular innovation projects to their success, a comparison of output effects of projects funded before and during the crisis is not possible with the data at hand. A second limitation is our focus on German firms. Germany is one of the biggest R&D spenders in the world. It is heavily specialised in manufacturing industries and has a high proportion of business R&D. Germany's R&D policy during the crisis may not work for other countries where business R&D as a stock is lower and more volatile. It would be of great policy interest to compare different innovation policies during the crisis and their efficacy for a set of countries with different characteristics. An additional limitation refers to the unobserved decision rules of the firms and the funding agency. As we mentioned in Section 2.4.1, the rules according to which the funding agency decides on subsidising is unknown to us. In addition, we also cannot observe the reason(s) and the number of firms actually applying for subsidy support. Both types of unobservability are likely to limit the extent to which the selection stage can be modelled because propensity score matching relies on the selection based on (only) observable characteristics. Furthermore, it would be of high interest to test the efficacy of research versus development subsidies during the past economic crisis. Unfortunately, our data set is not detailed enough to provide such an analysis, but other survey data such as the Flanders R&D survey would allow for that (see Hottenrott et al., 2014). Another important factor that we cannot take into account due to data limitations is the effect of collaboration on the efficacy of R&D subsidies during the crisis (Czarnitzki et al., 2007). This is another important avenue for future research. At last, the limitations of the matching approach should be acknowledged. Most important is the fact that the matching method only accounts for selection based on observable characteristics. In light of the previous literature that finds similar results for the direct R&D subsidy program in Germany independent of the method that has been employed (see e.g. Almus and Czarnitzki, 2003; Czarnitzki et al., 2007; Hussinger, 2008), we believe that this is a minor issue in our particular context.

[18] See Brautzsch et al. (2015) for a study examining R&D output effects during the most recent crisis in Germany.

2.A Appendix

Table 2.A.1: Comparison of the descriptive statistics between the pre-crisis and (post-) crisis periods

	Pre-crisis period (2006-2008) N = 6,172		Crisis-/post-crisis period (2009-2010) N = 4,335		t-test
	Mean	Std.dev.	Mean	Std.dev.	
Covariates:					
Sub_t-4	0.036	0.187	0.041	0.198	
Patemp	0.004	0.030	0.004	0.033	
Lemp	3.230	1.094	3.143	1.097	***
Foreign	0.054	0.226	0.043	0.202	***
Export	0.449	0.497	0.433	0.495	*
Group	0.226	0.418	0.203	0.402	***
Lage	3.033	0.866	3.088	0.839	***
East	0.345	0.476	0.341	0.474	
Sales_growth	5.287	9.349	-1.172	16.691	***
Credit	225.297	65.640	225.888	62.202	
Credit_mvd	0.034	0.182	0.034	0.181	
Outcome variables:					
RD	0.110	1.055	0.086	0.534	
PRIVRD	0.098	0.942	0.074	0.508	*
RDINT	0.019	0.089	0.019	0.085	
PRIVRDINT	0.014	0.076	0.013	0.065	
RDEMP	0.002	0.009	0.002	0.007	
PRIVRDEMP	0.001	0.008	0.001	0.006	

Source: PROFI data base and MIP; authors' own calculation.

Note: * p<0.1; ** p<0.05; *** p<0.01.

Table 2.A.2: Full table of Table 2.3

	Coefficients	Std.err.
Sub_t-4	**2.187*** **	(0.118)
Patemp	**4.568*** **	(0.700)
Lemp	**0.149*** **	(0.032)
Foreign	0.050	(0.127)
Export	**0.775*** **	(0.075)
Group	**-0.243*** **	(0.084)
Lage	**-0.273*** **	(0.042)
East	**0.245*** **	(0.065)
Sales_growth	-0.003	(0.004)
Credit	**-0.002** **	(0.001)
Credit_mvd	**-0.686*** **	(0.243)
Industries:		
Mining	**-1.130*** **	(0.294)
Low-tech manuf.	**-0.984*** **	(0.098)
High-tech manuf.	**-0.423*** **	(0.099)
Energy/water/recycl.	**-1.012*** **	(0.163)
Wholesale	**-1.909*** **	(0.356)
Transportation	**-1.389*** **	(0.202)
ICT	-0.171	(0.117)
Consulting/advert.	**-0.800*** **	(0.180)
Years:		
2007	-0.069	(0.074)
2008	**-0.293*** **	(0.074)
2009	0.117	(0.398)
2010	0.328	(0.398)
Constant	**-0.645** **	(0.260)
Controlling for period differences:		
Sub_t-4_period	-0.199	(0.177)
Patemp_period	**12.221*** **	(2.045)
Lemp_period	-0.025	(0.049)
Foreign_period	-0.250	(0.202)
Export_period	-0.009	(0.111)
Group_period	0.139	(0.124)
Lage_period	**-0.141** **	(0.062)
East_period	**-0.353*** **	(0.096)
Sales_growth_period	0.005	(0.004)
Credit_period	0.001	(0.001)
Credit_mvd_period	0.046	(0.382)
Mining_period	-0.563	(0.610)
Low-tech manuf._period	**0.256***	(0.150)
High-tech manuf._period	**0.372** **	(0.152)
Energy/water/recycl._period	0.129	(0.247)
Wholesale_period	0.523	(0.463)
Transportation_period	**0.554** **	(0.275)
ICT_period	0.092	(0.178)
Consulting/advert._period	0.528**	(0.233)
Observations	10,527	
Log-likelihood	-1,968	
McFadden's R2	0.411	
Time dummies (chi2):	**24.26*** **	
Industry dummies (chi2):	**183.6*** **	
Period interactions (chi2):	**77.26*** **	

Note: * p<0.1; ** p<0.05; *** p<0.01.

Table 2.A.3: OLS regression of the outcome variables on subsidy receipts

	RD	RDINT	RDEMP	PRIVRD	PRIVRDINT	PRIVRDEMP
Sub	**0.812****	**0.138*****	**0.011*****	**0.652****	**0.092*****	**0.007*****
	(0.339)	(0.017)	(0.002)	(0.286)	(0.015)	(0.002)
Sub (2007)	**-0.426****	**-0.029***	**-0.003****	**-0.412***	**-0.039****	**-0.004****
	(0.214)	(0.017)	(0.002)	(0.212)	(0.015)	(0.002)
Sub (2008)	-0.106	-0.028	0.000	-0.066	-0.027	0.000
	(0.142)	(0.020)	(0.002)	(0.144)	(0.018)	(0.002)
Sub (2009)	**-0.615***	**-0.059*****	**-0.004***	**-0.525***	**-0.052*****	**-0.003***
	(0.344)	(0.021)	(0.002)	(0.292)	(0.018)	(0.002)
Sub (2010)	**-0.567***	**-0.046****	**-0.004***	**-0.491***	**-0.046*****	**-0.004****
	(0.341)	(0.020)	(0.002)	(0.289)	(0.017)	(0.002)
Sub_t-4	0.042	0.030	0.002	0.065	0.028*	0.002
	(0.300)	(0.019)	(0.002)	(0.251)	(0.017)	(0.002)
Patemp	**3.061****	**0.651*****	**0.066****	**2.832****	**0.569****	**0.059****
	(1.279)	(0.245)	(0.028)	(1.201)	(0.241)	(0.026)
Lemp	**0.104*****	-0.001	0.000	**0.095*****	0.001	0.000
	(0.031)	(0.001)	(0.000)	(0.026)	(0.001)	(0.000)
Foreign	0.243	-0.004	0.001	0.216	-0.003	0.001
	(0.186)	(0.006)	(0.001)	(0.156)	(0.005)	(0.001)
Export	-0.011	**0.010*****	**0.001****	-0.008	**0.010*****	**0.001*****
	(0.023)	(0.003)	(0.000)	(0.021)	(0.003)	(0.000)
Group	-0.037	-0.004	-0.000	-0.024	-0.002	-0.000
	(0.041)	(0.003)	(0.000)	(0.037)	(0.003)	(0.000)
Lage	-0.035	**-0.003****	**-0.000****	-0.030	-0.001	**-0.000****
	(0.027)	(0.001)	(0.000)	(0.023)	(0.001)	(0.000)
East	-0.000	0.004	0.000	-0.003	**0.005***	0.000
	(0.036)	(0.003)	(0.000)	(0.031)	(0.003)	(0.000)
Sales_growth	-0.001	0.000	-0.000	-0.000	0.000	-0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Credit	-0.000	0.000*	-0.000	-0.000	**0.000***	-0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Credit_mvd	-0.104	**0.016****	0.001	-0.086	0.013	0.000
	(0.139)	(0.008)	(0.001)	(0.120)	(0.008)	(0.001)
Constant	-0.106	-0.004	0.001	-0.112	**-0.014***	-0.000
	(0.091)	(0.008)	(0.001)	(0.080)	(0.008)	(0.001)
Observations	10,527	10,527	10,527	10,527	10,527	10,527
Time dummies (F):	1.510	**3.01****	1.910	1.610	**2.64***	2.010
Industry dummies (F):	**4.63*****	**8.73*****	**9.89*****	**4.77*****	**8.01*****	**9.68*****
Period interactions (F):	0.930	1.160	1.340	0.900	1.260	1.360

Source: PROFI data base and MIP; authors' own calculation.

Note: * p<0.1; ** p<0.05; *** p<0.01; robust standard errors in parentheses.

Table 2.A.4: Additional test on the comparison of treated firms before and after the crisis

	Treated before 2009 N = 520	Treated after 2008 N = 496	t-test	p-value
	Mean	Mean		
Additional indicators:				
Log of labour productivity	-2.349	-2.318		0.502
Investments in tangible assets (in million EUR)	3.017	3.034		0.980
Capital intensity	0.041	0.044		0.608
Innovators	0.829	0.855		0.256
Log(new product sales + 1 EUR)	0.032	0.520		0.324

Source: PROFI data base and MIP; authors' own calculation.

Note: * p<0.1; ** p<0.05; *** p<0.01.

Chapter 3

Adjustment Effects of Innovation Investment on Innovation Performance over the Business Cycle[19]

3.1 Introduction

The global economic crisis of 2008/2009 had substantial impacts on the economy. Most attention has been paid to financial markets, monetary policy and government deficits. However, other types of economic activities, which have a substantial impact on future growth prospects, were heavily affected as well. One of these is innovation, i.e. productivity-enhancing technological change (see Filippetti and Archibugi, 2011). Previous research on the relationship between innovation and business cycle fluctuations has shown that innovation expenses tend to react pro-cyclically due to cash-flow dependency as resource allocation on innovation projects is often simultaneously determined with firm performance (see e.g. Himmelberg and Petersen, 1994; Mulkay et al., 2001). If a firm's cash flow diminishes due to an unexpected drop in sales, funding of innovation becomes difficult and some projects may need to be stopped whereas others need to be scaled down. An unplanned reduction in innovation effort due to an exogenous shock can have negative effects on both firms and the economy as a whole. From a firm perspective, stopping or downscaling of innovation projects can harm a firm's competitiveness if the pipeline of new products dries out and efficiency gains from new technologies remain unutilised. From a macroeconomic perspective, lower investment in innovation may reduce the total knowledge stock of an economy, which is likely to reduce future productivity growth. For these reasons, overcoming the recent crisis and ensuring long-term competitiveness is a major concern for both firms and policymakers. However, it is not the innovation investment *per se* that drives a firm's competitive position and performance, respectively. Instead, the innovation output and the corresponding success of newly implemented and applied technologies is decisive for growing market shares and sales growth (Crépon et al., 1998; Mairesse and Mohnen, 2010).

[19] This chapter is based on the following article: Hud, M., Rammer, C., 2015. Innovation budgeting over the business cycle and innovation performance. ZEW Discussion Paper No. 15-030, Mannheim. We are grateful to Martin Carree, Dirk Czarnitzki, Ulrich Kaiser, Pierre Mohnen, Hiroyuki Okamuro, Bettina Peters, Andrin Spescha and Reinhilde Veugelers for comments of earlier versions of this article. Furthermore, we would like to thank the participants of ZEW's industrial economics lunch seminar, of the PhD Workshop in Maastricht 2012, of the ZEW/MaCCI Conference on Innovation and Patenting 2013, of the EARIE 2013 and of the SEEK Conference 2015 in Mannheim.

In this chapter, we analyse the performance effects of product innovations of firms that increase their innovation investment over the business cycle. In particular, our target is to investigate whether firms that positively adjusted (i.e., increased) their innovation expenses during the recent crisis could increase their post-crisis product innovation performance or not. Conducting innovation activities is risky. It is a priori not clear whether or not expanding this type of risky investment particularly during crisis periods pays off afterwards. This means, the ex-post success of product innovations may even be less predictable during periods of economic uncertainty than during positive growth periods. The post-crisis success may essentially depend on the type of the implemented product innovation. For instance, new-to-the-market products may lead to higher sales growth if they were implemented after a crisis period when there are more opportunities to take and less rivals to compete with as compared to the case if they were implemented after a boom period. For this reason, we differentiate product innovation success into two measures, (i) the sales share of new-to-the-market products and (ii) the sales share of new-to-the-firm products. To the best of our knowledge, our study provides first evidence as to the business cycle dependency of the efficacy of an increase in innovation investment on product innovation performance.

In this chapter, we use a panel data set of German firms operating in a variety of manufacturing and service sectors. Our data contain information on firms' innovation expenses, innovation success and other business-related characteristics. We observe the period of 2006 to 2012, which covers not only the most recent economic crisis period of 2008/2009 but also the pre-crisis (2006-2007) and post-crisis (2010-2012) years. The most recent crisis became critical for the majority of German firms in late 2008 while the business climate already started to recover in late 2009. The year 2009 was the year with the largest drop of Germany's GDP since World War II. With data from these different periods at hand, we are able to compare the effects of the firms' counter-cyclical innovation investment adjustments with adjustment effects accruing during economically stable growth periods. We measure the firms' adjustment of innovation investment as an annual change of firms' innovation intensities (i.e. innovation expenses over sales). Its business cycle dependency is accounted for by interacting the adjustment term with three dummy variables each of them representing different growth periods, i.e. high growth, medium growth and low growth. We do not only measure these growth periods by annual GDP growth. An economy-wide crisis period may not be as crucial for innovation success as the economic situation of a firm's focal industry, i.e. its primary sales market. Therefore, we also use industry-based interaction terms that allow us to measure the efficacy of increasing innovation investment in the case the firms' focal industry is high-, medium- or low-growing. Innovation success is represented by two different variables that consider the degree of product innovations' novelty, i.e. the sales share of products that are new to the market and the sales share of products that are only new to the firm (see Mairesse and Mohnen, 2010). As our performance variables solely depict product innovation success, we restrict our analysis to those firms that actually conduct product innovation activities.

By estimating Fixed Effects models, we find that a positive adjustment of innovation investment during high and medium growth periods increases the firms' innovation performance. However, these effects only hold for the sales share of products that are new to the market but not for the corresponding sales share of new-to-the-firm products. Furthermore, we find that a positive adjustment of innovation investment during the crisis could increase the post-crisis innovation success if the crisis was measured according to GDP and industry growth. However, the positive adjustment effect turns out to be only significant in the case of GDP-based interaction terms. Our results suggest that (i) performance-enhancing effects of increasing innovation investment can lead to higher innovation success even during crises times and (ii) this effect essentially depends not only on the type of innovation success but also on the considered growth period and on the level the growth periods are measured at (national level vs. industry level).

The rest of the chapter is organised as follows. Section 3.2 gives an overview on the literature on business cycle impacts on innovation and discusses our hypotheses. Section 3.3 explains the conceptual framework and describes the panel data set we use. Section 3.4 presents estimation results and robustness checks, while Section 3.5 concludes.

3.2 Literature review and hypotheses

3.2.1 Cyclicality of innovation input

The literature on the relationship between the business cycle and innovation has largely focused on the cyclicality of innovation input. Although we do not directly analyse that cyclical dependency but investigate the performance effects of pro- and counter-cyclical innovation investment, we present the basic concepts in the following.

One of the most prominent analyses of business cycle fluctuations and innovation was conducted by Schumpeter (1942). In his theory of creative destruction, recessions reorganise markets and encourage firms to innovate, whereas firms unable to innovate or to restructure exit the market (Caballero and Hammour, 1994). This “cleansing” effect, which indicates a counter-cyclical innovation pattern, is similar to the opportunity cost effect. According to theoretical contributions, firms shift more resources to productivity-enhancing activities, such as innovation, during recessions than during boom periods. The underlying idea is that firms can use their human and physical resources either for production purposes or for productivity improvements. In recessions, the opportunity costs in terms of marginal forgone profits of innovation investment as compared to (short-term) capital investment are lower than in boom periods. For this reason, declining opportunity costs are expected to cause a counter-cyclical innovation pattern (see e.g. Bean, 1990; Gali and Hammour, 1991; Saint-Paul, 1993; Aghion and Saint-Paul, 1998). This counter-cyclical prediction, however, does not fit to the pro-cyclicality found by, for instance, Fatas (2000), Wälde and Woitek (2004) and Comin and Gertler (2006) who observe long-time series on a country level. Whereas Fatas (2000) and Comin and Gertler (2006) focus on the USA, Wälde and Woitek find a pro-cyclical pattern among the G7 countries. Hence, the raw data reveal evidence that firms on average expand their innovation expenses during boom periods than during recessions. This pro-cyclicality may be largely caused by the innovators’ dependency on internal cash flow (profits) to fund innovation projects (see e.g. Hall, 1992; Himmelberg and Petersen, 1994; Harhoff, 1998; Mulkay et al., 2001; Rafferty and Funk, 2008). Innovators cannot strongly rely on external lending options due to asymmetric information between innovators and lenders (Hall, 2002). In general, the level of cash flow is higher in boom periods than in recession periods.

More recent contributions find asymmetric effects of innovation investment over the business cycle. In particular, the role of financial constraints determines the pro- and counter-cyclicality of innovation investment. Aghion et al. (2010) find an asymmetric effect of long-term investment.[20] They use data of 21 OECD countries observed between 1960 and 2000. According to their results, the share of long-term investment relative to total private investment is pro-cyclical in countries that have sufficiently tight credit markets. Ouyang (2011) examines the opportunity cost hypothesis with respect to the cyclicality of R&D investment. She uses industry-level data of 20 US manufacturing industries covering the period of 1958 to 1998 and finds R&D to be pro-cyclical in general. In addition, by using

[20] Aghion et al. (2010) do not use an innovation investment indicator but long-term investment, which serves as a proxy variable for growth-enhancing investment types.

more aggregated indicators her results disclose an asymmetric response of R&D investment. That is, a positive demand shock causes R&D expenses to decrease due to rising opportunity costs, whereas a negative demand shock decreases R&D investment due to liquidity constraints. Despite this asymmetric drift, Ouyang (2011) argues that the liquidity constraint is the key determinant in explaining the general result of pro-cyclical R&D effort. Aghion et al. (2012) use a sample of 13,000 French firms that were observed during 1993-2004. The authors' results show that credit-constrained firms increase their R&D expenses in cyclical upturns compared to non-constrained firms, underpinning the hypothesis of pro-cyclicality. This relationship, however, turns to be counter-cyclical in the case of non-constrained firms.[21]

3.2.2 Cyclicality of innovation output

One of the most important theoretical contributions has been developed by Shleifer (1986). In his model, Shleifer (1986) focusses on the timing of the commercialisation of innovation. He assumes that inventions are exogenously developed and arrive at a constant rate. Innovators are profit-maximising and time the implementation of innovations accordingly. Due to entering imitators eliminating all monopoly profits, the innovators delay the implementation until a boom emerges. Barlevy builds a Schumpeterian endogenous growth model and predicts R&D to be pro-cyclical, even though it is not socially optimal. He assumes R&D investment and the implementation of innovation to occur contemporaneously due to firms' impatience. This means, the timing of R&D determines the timing of the innovation itself. Like Shleifer (1986), Barlevy (2007) assumes innovators to be profit-seeking and imitators are expected to emerge immediately after new ideas have been discovered. To circumvent the profit risk, innovators shift their innovations to upturn periods. Francois and Lloyd-Ellis (2003) endogenize innovation in Shleifer's model. In their model, innovative effort produces inventions that can be stored and be held secret. This allows a strategic delay of the implementation of innovations. During recessions, the innovators do delay and wait until the boom arrives but they also increase their innovative effort. When the boom arrives, the innovators will gain from their monopoly profits and will shift their resources from innovative effort to production. In a later paper, Francois and Lloyd-Ellis (2009) predict R&D and the implementation to be pro-cyclical but occurring at different phases. They assume that R&D produces ideas that first have to be incorporated in products before they can be implemented as an innovation. According to the model, the value of the ideas is highest during an expansion period, which follows an implementation boom period. Hence, R&D effort is maximised during expansions. During recessions, when the demand slows down, the innovators reduce their R&D activities and increase their search effort so that they can match applications with the ideas. The search effort reaches its peak before the implementation boom arises.

Fabrizio and Tsolmon (2014) take the approaches of Shleifer (1986), Francois and Lloyd-Ellis (2003, 2009) and Barlevy (2007) directly into account when empirically analysing the pro-cyclicality of R&D investment and innovation output. Their analysis is based on Compustat, NBER Patent Data, the Carnegie Mellon Survey (CMS) and the NBER Manufacturing and Productivity database and covers the years 1975 to 2002. The R&D indicator is measured as the first-difference of the log of R&D expenses. Innovation output is measured as the number of patents. Fabrizio and Tsolmon (2014) also include a measure that indicates industry-level patent efficacy to test whether the imitators' threat leads to more pro-cyclicality or not. To separate the timing of R&D and innovation output the authors include an indicator that measures the speed with which innovations are introduced in the firms' focal industry. Their

[21] Following Aghion et al.'s (2012) approach, Bovha-Padilla (2009) and López-Garcia et al., (2012) find a very similar asymmetric effect.

findings are consistent with the pro-cyclical pattern of R&D effort and innovation output. According to their results, the timing of innovation is more pro-cyclical the stronger the threat of imitators in the firms' focal industry. However, the pro-cyclicality of innovation output does not depend on the industry-level speed of the introduction of innovations. In contrast, a higher speed leads to more pro-cyclicality of R&D investment. Their results suggest (i) firms will shift the implementation of innovations to growth periods and (ii) if innovations do not diminish in value very quickly firms will tend to shift R&D investment to downturn periods.

In a more general empirical approach, Geroski and Walters (1995) find evidence for the pro-cyclicality of innovation output as well. They investigate the innovation pattern of UK firms over the period 1948-1983 and find that cyclical fluctuations Granger cause the total number of innovations and the number of patents. In addition, the authors show that the firms' innovation activities tend to cluster during boom periods.

3.2.3 Hypotheses

The paper by Fabrizio and Tsolmon (2014) seem to be closest to our analysis. The major differences are that (i) they use a mere innovation output measure (patent counts), which does not give any information on the success of innovation and (ii) they do not consider that the firms' efficacy of R&D investment may also vary over the business cycle. To the best of our knowledge, there is no empirical study yet that examines the effect of increasing innovation investment on the product innovation success with respect to different business cycle periods.

We start from the basic assumption that investment in innovation has positive returns, which means that innovation activities result in higher innovation and firm performance, respectively. There is ample evidence in the literature that this basic assumption holds (see e.g. Crépon et al., 1998; Hall, 2011). Under normal economic conditions, i.e. the economy is positively growing, firms will attempt to maintain an optimal level of innovation investment allowing them to steadily fill their pipeline of new products, continuously advance their production methods and keep pace with technological change. This optimal level will largely depend on the type of technical change and the competitive environment under which firms operate. As both factors rarely change from year to year, firms' optimal investment level for innovation will be largely constant in the short run. Positive adjustments of firms' innovation investment will primarily reflect changes in strategic priorities of the firms, e.g. entering new product markets or new technologies. Hence, under normal economic conditions more innovation input also leads to more innovation output and success.

For a crisis period, this typical relationship may be impaired. It is a priori not clear whether a short-term increase in innovation investment will also translate into a short-term (though lagged) increase in innovation success. An economic crisis induced by a short and adverse shock as in 2008/2009 is typically characterised by unexpectedly dropping sales levels and deteriorating profits, which calls for cost cuts that challenge the firms' attempt to maintain their target level of innovation. In such a situation, most firms will react by reducing their expenses along with diminished returns, including expenses for innovation projects. Such cost cuts are likely to result in stopping (some) innovation projects. But firms cannot easily re-start them in the following period to achieve immediate results (in terms of new products) as innovation projects typically stretch over a multi-annual period until they are successfully completed (see Aschhoff et al., 2013, p. 65, on the average length of innovation projects). Furthermore, stopping some projects reduces the firms' portfolio of new products. This limits the firms' ability to react on changing consumer preferences and competitor strategies in the post-crisis period. In particular, this applies to an uncertain market environment and to rapidly changing demand, which is typically the case in a crisis period (Devinney, 1990; Klingebiel and Rammer, 2014). If cost cuts in innovation expenses reduce the budget per project, the quality of the outcome of each project may decline. This means, new products may be less competitive due to less advanced and tested technological features. Hence, economic crises causing financing restrictions are likely to hamper innovation investment of firms, which may suffer from a lack of innovation sales and a competitive disadvantage after the crisis. A similar argument refers to the product demand. Even if firms increase their innovation investment during a crisis to develop and market new products, respectively, the new products' success may not arise. For instance, customers may hesitate to buy the new products directly after a crisis because they are typically more expansive than already established products while the wage level still stagnates.

In contrast, there are also some reasons why the positive input-output relationship of innovations still holds during crisis periods. One argument refers to the opportunity cost effect discussed in Section 3.2.1. Accordingly, there are firms that increase their innovation expenses counter-cyclically due to lower opportunity costs of innovation investment. For instance, employees who may have less production-related workload due to a crisis-induced decline of orders could be shifted to innovation projects. This implies that at least a certain fraction of firms expand their investment in innovations, which should lead to more and qualitatively superior new products as compared to firms that reduced their innovation expenses. In this case, the investment increase should lead to higher post-crisis innovation success. Hence, firms that increase their innovation investment during a crisis may gain a competitive advantage as compared to firms that decrease their innovation investment. These firms are likely to be able to exploit a larger product portfolio during the post-crisis period than firms that downsized their innovation investment.

A second argument is particularly relevant to crises similar to the one from 2008/2009, i.e. a short and deep recession followed by a strong recovery. Firms that counter-cyclically invest in innovations allowing them to introduce new products can substantially benefit as the economy may experience a significant upswing in demand after the crisis. These firms are likely to have higher new product sales with the result that their competitive position may be stronger than before. In a similar line of reasoning, recessions are times of reorganisations or "cleansing" in which less productive (innovative) firms drop out and the more productive firms survive. This would "automatically" lead to positive effects of innovation expansion during a crisis. However, recently it has been shown that firm entry indeed is pro-cyclical but that firm exit does not necessarily increase during recessions (Bilbiie et al., 2012; Lee and Mukoyama, 2015). This implies that (existing) firms have to face fewer (new) competitors during recessions. Hence, an increase of their innovation investment during a crisis may strengthen their future competitive position even more than during a positive growth environment. They have potentially more opportunities to exploit in a crisis' aftermath.

Despite potential reasons hampering the positive relationship, we still expect that firms able to increase their innovation investment during a crisis benefit from higher innovation success in the following upturn period.

H1: During a crisis, an increase in innovation investment translates into an increase in post-crisis innovation success.

The positive adjustment effect of innovation investment on innovation success just discussed is most likely particularly pronounced for new-to-the-market products. This type of products is more risky with their expected return being more uncertain but also more promising than products new to the firm. Furthermore, it is also more difficult, costly and time-consuming to solve the technological challenges inherent to new-to-the-market products. Hence, under normal economic conditions more innovation investment should lead to a higher sales share of new-to-the-market products.

This positive relation may not necessarily hold during crisis periods. Firms may refrain from investing in the development and commercialisation, respectively, of new-to-the-market products due to their uncertain success and relatively high costs during a crisis period. Therefore, firms may rather be inclined to reduce their effort for those types of product innovations and shift their financial resources to, for instance, the implementation of new-to-the-firm products. This asymmetric response may rather lead to higher innovation success of products new to the firm. On the contrary, it can be a successful strategy for firms to increase their investment related to new-to-the-market products during crises. As probably most of the firms reduce this innovation investment during crises, they may lack (radical) new products that could create a competitive advantage for them in the subsequent economic upturn. Hence, firms that increase their innovation investment related to new-to-the-market products during crises should be able to seek new growth opportunities afterwards as the competition may be lower than during other growth periods. In the post-crisis recovery period, ambitious innovators may be more able to dominate their markets or are at least more resilient in the face of their (new) competitors. For this reason, we would expect that higher innovation investment during a crisis would increase the sales share of new-to-the-market products.

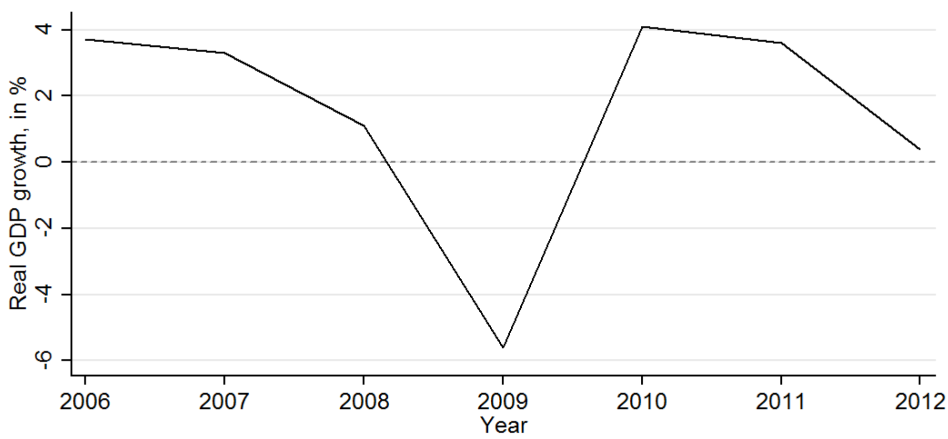
H2: An increase in innovation investment during a crisis leads to a higher sales share of new-to-the-market products in the post-crisis period.

3.3 Methodology and data

3.3.1 Business cycle 2006-2012 in Germany

From a business cycle perspective, one can divide our observed period, 2006-2012, into three separate periods (see Figure 3.1). The first period, the years 2006 and 2007, was characterised by a prosperous macroeconomic environment in Germany with annual GDP growth rates ranging between 3% and 4%. The second period, the period of the most recent economic crisis, covers the years 2008 and 2009. Although the year 2009 represents the severest economic crisis in German post-war economic history, with a decline in real GDP by 5.6%, the recent crisis period already started for the firms in the second half of the year 2008. As we use annual values, we refer to the crisis year as the year 2009.

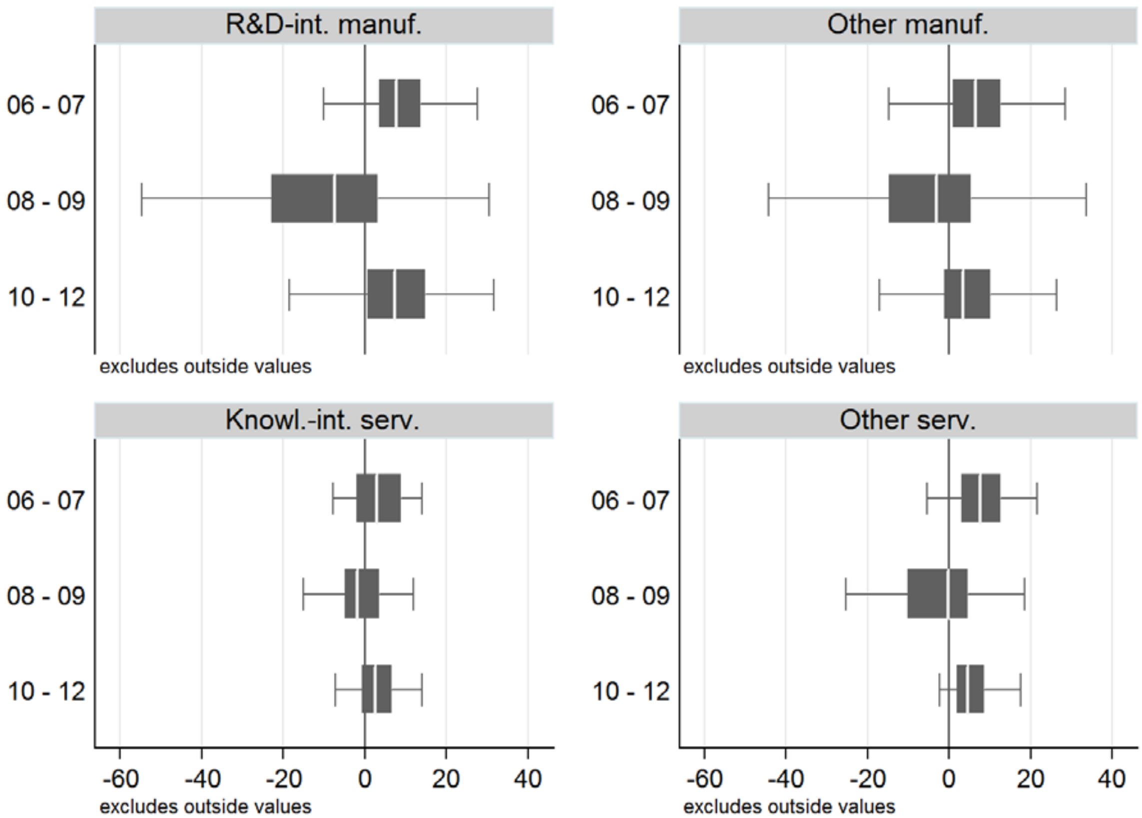
Figure 3.1: GDP growth of Germany between 2006 and 2012, in %



Source: Federal Statistical Office of Germany (Destatis); authors' own calculation.

The last period, the years 2010 to 2012, was a time of economic upswing with real GDP growth rates exceeding again 3% in 2010 and 2011. The GDP growth of 2012 already slowed down significantly. However, GDP growth may only be a rough business cycle indicator from a firm perspective as it only represents an average annual value across all industries. It does not directly account for heterogeneous industry-specific positive or negative developments. For instance, while many industries have been severely affected by the shock in 2009, some industries have already been affected in 2008 and some have not substantially been affected. Therefore, a more accurate economic indicator refers to a firm's focal industry, i.e. the product market a firm generates most of its sales in. Figure 3.2 presents box plots for the sales growth rates in each observed period, separated by highly aggregated industry classifications, i.e. R&D-intensive manufacturing (R&D-int. manuf.), other manufacturing (other manuf.), knowledge-intensive services (knowl.-int. serv.) and other services (other serv.).[22] The median values of all industries for the pre- and post-crisis periods are positive, which indicates an average growth of these industry aggregates. In contrast to the positive growth periods, the median values for the crisis period are below zero. This indicates an industry-wide sales drop, on average. However, the variance of the sales growth rates is very high compared to the pre- and post-crisis periods. This is a clear evidence for the heterogeneous impact of the crisis on the industry level.

Figure 3.2: Industry-level sales growth between 2006 and 2012, in %



Source: Destatis and Mannheim Innovation Panel (MIP); authors' own calculation.

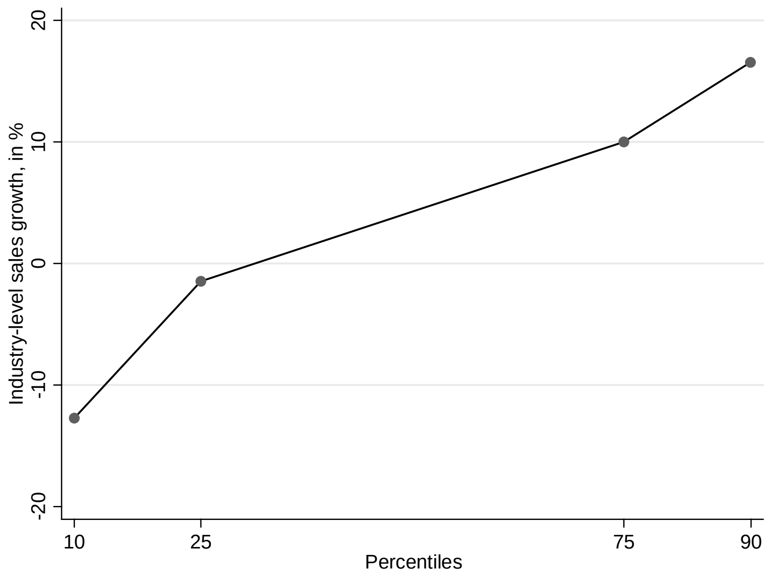
Note: The left axes refer to the pre-crisis period (2006-2007), the crisis period (2008-2009) and the post-crisis period (2010-2012). The bottom axes depict the industry-specific sales growth in %.

Hence, using mere time dummy variables to identify crisis effects may not be a reliable strategy. Therefore, we use growth dummies based on GDP growth but also growth dummies

[22] We use that highly aggregated classification for the sake of simplicity. Using more disaggregated information discloses stronger heterogeneities.

based on the firms' focal industry annual sales growth. We constructed three dummy variables indicating whether the firms' focal industry was high-growing ($High\_growth_{t|t-1}$), medium-growing ($Medium\_growth_{t|t-1}$) or low-growing ($Low\_growth_{t|t-1}$) between t and t-1. In so doing, we constructed two different sets of binary dummy variables. On the one hand, considering a more strict definition of high- and low-growing industries, we used the lowest and highest decile of the industry-level sales growth rate as the lower and the upper bound (thresholds). On the other hand, for a more tolerant definition of high- and low-growing industries, we used the lowest and highest quartile of the industry-level sales growth rate as thresholds. Figure 3.3 shows the plotted percentiles of the industry-level sales growth rate. That is, 10% of the growth rates are smaller than -12.7%, 25% of the growth rates are smaller than -1.4%, 75% of the values are smaller than about 10%, whereas 90% of the values are smaller than 16.5%. Table 3.1 presents an overview on the two sets of dummy variables. For instance, regarding the strict definition, an industry is considered as high-growing if its annual sales level increased by more than 16.5% in t compared to t-1. An industry is considered as low-growing if its sales level decreased by more than -12.7% in t compared to t-1. The annual sales level in a medium-growing industry did not decrease by more than -12.7% and did not increase by more than 16.5%. To be able to compare these results with the general demand condition in Germany, we also estimate three dummy variables equivalently measuring high, medium and low growth according to Germany's GDP growth rates and use 0% and 3% as our thresholds (see Table 3.1). Hence, we have three sets of dummy variables each of them including three growth dummies.

Figure 3.3: Plotted percentiles of annual industry-level sales growth during 2006-2012, in %



Source: Destatis and MIP; authors' own calculation.

Table 3.1: Business cycle indicators, in %

	Industry-level sales growth		GDP growth
Thresholds:	Strict (10%; 90%)	Tolerant (25%; 75%)	
High_growth	> 16.5	> 10	> 3
Medium_growth	>= -12.7 & <= 16.5	>= -1.4 & <= 10	>= 0 & <= 3
Low_growth	< -12.7	< -1.4	< 0

Source: Destatis and MIP; authors' own calculation.

Note: low (medium) growth according to the GDP indicator appeared in 2009 (2008), high growth periods appeared in the remaining years.

3.3.2 Empirical model

Our analysis rests on a firm-level innovation performance model. The success of firm *i*'s product innovations in year t+1, which denotes our dependent variable ($IS_{ij,t+1}$), refers to the success of two different types *j* of product innovations. In the literature, different concepts of innovative ambition have been proposed, such as radical innovations (based on radically new technology) and disruptive innovations (innovations that change the way markets operate). Instead, we differentiate the product innovations by the degree of novelty for the firms' customers (see Mairesse and Mohnen, 2010). Accordingly, we denote a product that is new to the market ("market novelty") if a new product was not available to a firm's customer before. If a new product is implemented by a firm but was not produced by that firm before but by its rivals, we denote it as a product only new to the firm ("product imitation"). As we focus on the success of market novelties and product imitations, respectively, we use the sales share of the respective type of product.

These sales shares depend on the level of expenses devoted to the development and introduction of product innovations divided by the lagged level of the firms' sales (i.e. innovation intensity – $Intensity_{i,t-1}$). To measure the effect of an increase in the level of innovation investment, we use the annual difference of the innovation intensity between the current and the previous year ($D\_intensity_{i,t|\,t-1}$). In order to identify the effects of the adjustment of innovation investment for different business cycle periods, we multiply the indicator $D\_intensity_{i,t|\,t-1}$ with each dummy variable representing different growth periods: $High\_growth_{t|t-1}$, $Medium\_growth_{t|t-1}$ and $Low\_growth_{t|t-1}$ (see Section 3.3.1). Each of the three sets of growth dummies is separately estimated for each dependent variable. This allows us to estimate a separate coefficient for the innovation adjustment term of each growth period. In addition, we estimate a vector of other firm characteristics ($X_{i,t}$) including, for instance, firm size, firm age, industry affiliation (based on NACE 2) and time dummies. Our empirical model reads as follows:

$$IS_{ij,t+1} = \beta_0 + \beta_1 Intensity_{i,t-1} + \beta_2 D\_intensity_{i,t|t-1} * High\_growth_{t|t-1} + \beta_3 D\_intensity_{i,t|t-1} * Medium\_growth_{t|t-1} + \beta_4 D\_intensity_{i,t|t-1} * Low\_growth_{t|t-1} + \beta_5 X_{i,t} + u_{i,t} \quad (3.1)$$

with $u_{i,t}$ being an unobserved error term that has an individual-specific time-invariant component and a time-variant component.

As the focus of the empirical analysis is on the share of new product sales, we restrict our sample to firms with product innovation activities. This includes (i) firms that introduced product innovations during t and t-2, (ii) firms that have conducted product innovation activities during t and t-2 but haven't completed any by the end of year t (i.e. these activities were still ongoing at the end of year t), and (iii) firms that conducted product innovation activities during t and t-2 but stopped them by the end of year t. This means, we expect our innovation variables not to suffer from (considerable) endogeneity biases as we already restrict our sample to firms that are innovation active. In this sense, we do not derive any conclusions for the total population of German firms but only for the product innovators.

In order to avoid a potential endogeneity bias due to unobserved individual time-constant heterogeneity, we estimate Fixed Effects (FE) models instead of pooled OLS models. Our dependent variables are continuously distributed. However, a significant share of firms reports a zero value of innovation success. One reason for this is that firms only had ongoing or stopped product innovation activities and did not introduce any new products between t and t-

2. In addition, firms may have introduced a new product but its success in terms of sales is still to come. Although these zeros are "true" zeros referring to a true failure of success (see Greene, 2012), we perform robustness checks by using Random Effects (RE) Tobit models to adjust for potential selectivity issues. One major criticism of the estimations of latent variable Random Effects models is the assumption of strict exogeneity (see e.g. Wooldridge, 2010; Greene, 2012). For this reason, Mundlak (1978) defines the time-invariant individual heterogeneity to be a function of a constant parameter, the time means of the time-varying variables and an i.i.d. error term with zero-mean that is uncorrelated with the explanatory variables.[23] In so doing, the assumption of strict exogeneity is "created". We apply the approach developed by Mundlak (1978) and include the time means of the time-varying variables as additional controls in our RE Tobit estimations. As some firms have even changed their focal industry, we include the time means of the industry dummies as well.[24]

A critical issue of estimating equation (3.1) relates to the way $D\_intensity_{i,t|t-1}$ is measured. We defined the innovation intensity as the ratio of innovation expenses (IE) over a firm's sales level (S). Taking the annual difference of it would mean to subtract the value of $Intensity$ in year t-1 from the value of $Intensity$ in year t. If we had constructed $D\_intensity_{t|\,t-1}$ that way we would have falsely measured it as, for instance, a large positive value of that difference could not have only been caused by higher innovation expenses but also by a decreased sales level while holding the level of the innovation investment constant. Therefore, we defined $D\_intensity_{i,t|\,t-1}$ as (IE_t - IE_{t-1}) / S_{t-1}. Hence, we study the impact of short-term economic fluctuations on adjustments in firms' innovation expenses. We believe that our measure for innovative effort to be superior over the absolute volume of innovation expenses as relating innovation investment to the previous sales level directly captures the firm's capacity to conduct innovation activities and it properly captures the extent of a firm's innovation adjustment to a (negative) shock.

3.3.3 Data

The empirical analysis is based on data from the Mannheim Innovation Panel (MIP). The MIP is conducted by the ZEW since 1993 on behalf of the German Federal Ministry for Education and Research (BMBF). The MIP is the German contribution to the European Commission's Community Innovation Surveys (CIS) and it is based on the methodology proposed in the Oslo Manual for collecting innovation data (OECD and Eurostat, 2005).[25] To construct our business cycle indicators, we use the publicly available data of the Federal Statistical Office of Germany (Destatis). Its data base allows us to get information on Germany's annual GDP growth rates as well as on sales indices on a 4-digit industry level, which we use to calculate the industry-level sales growth rates.[26] Furthermore, our sample also includes information taken from Creditreform, Germany's largest credit rating agency.

Almost all estimation variables are directly taken from the innovation survey data and rely on the standard measurements used in the CIS.[27] The share of market novelty sales refers to sales in year t+1 from products new to the market (*Market*) introduced in the previous three-year period. The corresponding sales share of product imitations is denoted by *Imit*. In addition, we include the sum of both sales shares to analyse the adjustment effect of innovation investment on the sales share of new products in general (*New*). Innovation investment covers the

[23] A more general approach can be found in Chamberlain (1980).

[24] The estimation results do not change when leaving out the mean values of the industry dummies.

[25] For further details see Aschhoff et al. (2013) and Peters and Rammer (2013).

[26] Not all industries are available on a 4-digit level. In these cases, we take the 2- and 3-digit levels, respectively.

[27] For the variables' definitions and descriptive statistics, see Table 3.A.1 in the Appendix.

expenses for research and development (R&D) as well as additional expenses required to develop and introduce new products such as the design, marketing, training, acquisition of external knowledge and technologies and acquisition of machinery and software needed to produce and distribute innovations. Our set of control variables includes several indicators. The direct impact of the business cycle on firms' resources is measured by the firm-level sales growth in t compared to the previous year t-1 (*Sales_growth*). We further include five size dummies (as measured by the number of employees), firms' age (*Age*) and the squared firm age (*Age2*) to capture potential non-linear age effects as well as firms' export market orientation (*Export*) and whether or not the firm belongs to an enterprise group (*Group*). In addition, we consider whether or not a firm conducts internal R&D on a continuous base and an occasional base (*R&D*), respectively, to better qualify a firm's innovation activities. In order to control for likely complementary effects of process innovations on product innovation success we also include a process innovation indicator (*Pc_innovator*). As the share of product innovation sales may also be affected by productivity effects, we also include firms' capital intensity (capital investment per employee), *Capital_intensity*. Furthermore, we have to control for potential financial constraints. For this reason, we use firms' credit rating indicator ranging from 1 (very good financial standing) to 6 (almost bankrupt), *Rating*.[28] Industry and time dummies control for industry-specific and time-specific variations in firms' capacity to generate product innovation success. In addition to our explanatory and control variables, the RE models of the robustness check further include the individual time-means of these variables based on the Mundlak (1978) approach. We label these means with a capital "M" at the beginning of each variable's name, e.g. *M_intensity_t-1* or *M_high*.

In order to observe firms' innovation investment and innovation performance over a longer period, we use seven consecutive survey waves. The resulting panel data set covers the period of 2006-2012. The total size of our sample includes 2,143 firms. As the panel data set is unbalanced, we do not have observations for each firm in each year.[29] The average number of observations per firm within the seven-year observational period is 3.7. This gives a total number of 8,095 firm-year observations.

3.4 Estimation results

Table 3.2 presents the results of the FE estimations. We run three different models: (i) one for the sales share of market novelties (*Market*), (ii) one for the sales share of product imitations (*Imit*) and (iii) one for the sum of both, i.e. the sales share of new products (*New*). Each estimated model includes interaction terms of the firms' innovation investment adjustments (*D_intensity_t|t-1*) and national- as well as industry-level growth indicators each of them representing high growth, medium growth and low growth periods.

According to Table 3.2, the one-year lag of the product innovators' innovation intensity does not show any significant effects. However, this insignificance is largely due to the way the individual heterogeneity is accounted for by FE regressions. The robustness checks unambiguously indicate strong significant effects for the average value of the product innovators' innovation intensity (see *M_intensity_t-1* in Table 3.3).[30] Even though the values are not significant, their magnitudes are positive. This indicates that a higher base level on a firm's innovation effort is also associated with higher (product) innovation success. The respective performance effects are even weakest for the sales share of product imitations. These results hold for the GDP-based interaction terms as well as for the interaction terms that are based on industry-level growth periods.

[28] The credit rating indicator and firm age are taken from Creditreform's data base.

[29] Possible reasons are entries and exits from the panel sample and irregular responses of the participating firms.

[30] Pooled OLS regressions (not presented in the chapter) also show strong significant effects of *Intensity_t-1*.

The estimates of our key variables support these findings. In the case of the GDP-based interaction terms, increased innovation investment during high and medium growth periods had significantly positive effects on the shares of new product and market novelty sales. Furthermore, we do not find a significant and positive effect on the sales share of product imitations. For this reason, it may be not the most promising decision for product innovators to increase their innovation investment related to product imitations. These results just assure that a positive adjustment of innovation effort increases the success of market novelties under normal economic conditions. More interesting, a counter-cyclical increase of innovation investment had a positive effect on the success of market novelties as well. If a product innovator expanded its innovation investment during the crisis year 2009, it could significantly increase its post-crisis innovation success.[31] In addition, this effect is even stronger than the performance effects found for high growth and medium growth periods. This means, a counter-cyclical innovation investment was more effective than a pro-cyclical innovation investment. These findings support our hypotheses H1 and H2.

Table 3.2: Effect of an adjustment of innovation investment on innovation success during different growth periods, FE model

Thresholds:	**10%; 90% (industry-based)**			**25%; 75% (industry-based)**			**GDP growth**		
Sales share of:	New	Market	Imit	New	Market	Imit	New	Market	Imit
Intensity_t-1	0.041	0.027	0.014	0.053	0.045	0.008	0.059	0.036	0.022
	(0.066)	(0.059)	(0.064)	(0.067)	(0.067)	(0.068)	(0.066)	(0.062)	(0.064)
D_intensity_t|t-1 in periods of:									
High_growth	0.020	0.092	-0.072	0.115	**0.188****	-0.073	**0.104***	**0.084****	0.020
	(0.076)	(0.061)	(0.069)	(0.086)	(0.080)	(0.061)	(0.053)	(0.036)	(0.046)
Medium_growth	**0.121*****	**0.098*****	0.023	**0.109****	**0.074****	0.035	**0.112***	**0.108****	0.003
	(0.046)	(0.029)	(0.037)	(0.046)	(0.030)	(0.035)	(0.064)	(0.053)	(0.036)
Low_growth	0.024	0.051	-0.027	0.113	0.094	0.018	0.159	**0.131***	0.028
	(0.109)	(0.069)	(0.117)	(0.095)	(0.063)	(0.103)	(0.112)	(0.075)	(0.109)
Constant	**0.581*****	0.078	**0.503*****	**0.580*****	0.069	**0.511*****	**0.581*****	0.077	**0.503*****
	(0.178)	(0.088)	(0.173)	(0.179)	(0.089)	(0.174)	(0.178)	(0.089)	(0.174)
Observations	4,238	4,238	4,238	4,238	4,238	4,238	4,238	4,238	4,238
Rho	0.912	0.836	0.903	0.913	0.837	0.905	0.913	0.835	0.904
Dummies:									
Time (F):	**9.640*****	0.960	**8.910*****	**9.910*****	1.130	**8.750*****	**10.04*****	0.980	**8.950*****
Industry (F):	**75.77*****	**25.47*****	**64.72*****	**66.89*****	**25.16*****	**56.65*****	**74.45*****	**25.14*****	**63.13*****

Source: Destatis and MIP; authors' own calculation.

Note: *** p<0.01, ** p<0.05, * p<0.1; standard errors – in parentheses – are clustered at the firm level; for full information on estimation results see Table 3.A.2 in the Appendix.

The basic results also hold in the case the interaction terms are based on industry-level sales growth. With respect to the more tolerant definition of the growth periods (25%; 75%), the estimates are quite similar to the GDP-based indicators. That is, increasing innovation investment during high and medium growth periods lead to higher sales shares of new products and market novelties, even though the effect of *High_growth* on *New* is not significant. According to the stricter definition (10%; 90%), only positive adjustments of innovation effort performed during medium growth periods could significantly increase the success of new products and market novelties. Like the estimates of the GDP-based indicators, the success of product imitations is not significantly affected by adjustments of

[31] Remember: Low growth measured by GDP growth only appeared in the year 2009.

innovation expenses, independent of the considered growth period. However, we cannot find any significant positive performance effects of counter-cyclical innovation investment, even though the effects are positive. For these cases, we do not find support for our hypotheses H1 and H2.

Our results suggest that a pro-cyclical innovation investment seems to has been a successful strategy for product innovators. In particular, if a positive adjustment of innovation effort had been combined with a stronger focus on the development and implementation of products new to the market, respectively, it could have been even more beneficial to the product innovators. Furthermore, a counter-cyclical innovation investment could increase the product innovators' innovation success as well. However, this positive counter-cyclicality is only found for the GDP-based indicators and not for the industry-based ones. This means that firms that shifted more financial resources to the development or introduction of market novelties in 2009 compared to 2008 had significantly higher innovation success in 2010.

This is a critical result as no counter-cyclical adjustment effects could be found for the industry-level indicators. Hence, it does not seem to be a promising strategy for a product innovator to expand its innovation investment in case only the demand in its focal industry is dropping. As discussed in Section 3.2.1, the main rationale for conducting counter-cyclical innovation investment is lower opportunity costs of innovative efforts compared to capital investment during recessions. The insignificant effect we find for the industry-level low growth interaction term implies that opportunity costs may have not been low enough during "industry-level crises" for a product innovator to benefit from a counter-cyclical innovation investment adjustment. However, opportunity costs may be sufficiently low in case the whole economy suffers from a crisis, i.e. if real GDP growth is negative. In such a situation, labour, capital and raw material markets will be affected by the economic slump. High-skilled labour and industrial inputs (from raw materials to equipment) will become more affordable and interest rates fall, favouring investment in general, and innovation expenses in particular. Furthermore, such effects are likely to be more pronounced if a crisis spreads across the entire world economy as happened in 2009. In this case, firms can gain, for instance, from lower oil prices, lower costs for new equipment, increased cross-border mobility of (high-skilled) labour and excess supply of cheap financial capital. As a result, we would expect the positive effect on market novelty success we find for the GDP-based low growth interaction term to be largely driven by product innovators the focal industry of which was not strongly affected by the 2009 crisis. These firms were probably able to fully exploit the strength/robustness of their focal industry and the relatively low opportunity costs. Therefore, a counter-cyclical innovation investment of product innovators may be only effective during an economy-wide crisis in the case the innovators' focal industry is expanding and not contracting.

Table 3.3 presents the results of the robustness check. We performed RE Tobit estimations by using the Mundlak (1978) approach requiring the estimation of the time means of the time-varying variables to account for individual heterogeneity. According to the results, a higher average level of the innovation intensity is positively and significantly related to product innovation success. A similar positive relationship for the average values of the interaction terms only holds for the estimates capturing the average pro-cyclical effects (*M_high* and *M_medium*). The average values of the counter-cyclical adjustment (*M_low*) are not significant and even negative in two cases. The estimates of our key interaction terms largely correspond to the estimated coefficients presented in Table 3.2. For instance, the sales share of product imitations is not significantly affected neither by a pro-cyclical nor a counter-cyclical innovation investment, whether or not growth is measured on the industry or the national level. In contrast, pro-cyclical innovation investment could significantly increase the subsequent success of new products and market novelties.

Table 3.3: Robustness check – RE Tobit model

Thresholds:	**10%; 90% (industry-based)**			**25%; 75% (industry-based)**			**GDP growth**		
Sales share of:	New	Market	Imit	New	Market	Imit	New	Market	Imit
Intensity_t-1	0.029	0.051	-0.008	0.013	0.066	-0.026	0.042	0.041	0.023
	(0.070)	(0.062)	(0.075)	(0.071)	(0.063)	(0.077)	(0.069)	(0.061)	(0.074)
D_intensity_t|t-1 in periods of:									
High_growth	-0.038	**0.249****	-0.118	0.073	**0.300*****	-0.090	0.057	**0.101*****	0.009
	(0.108)	(0.124)	(0.114)	(0.070)	(0.064)	(0.076)	(0.045)	(0.039)	(0.048)
Medium_growth	**0.072***	**0.117*****	-0.015	0.065	**0.083****	0.000	0.094	**0.127*****	-0.010
	(0.041)	(0.035)	(0.044)	(0.044)	(0.038)	(0.047)	(0.059)	(0.049)	(0.064)
Low_growth	-0.052	0.180	-0.125	-0.047	**0.144***	-0.118	0.028	**0.190****	-0.058
	(0.126)	(0.116)	(0.135)	(0.083)	(0.075)	(0.088)	(0.099)	(0.092)	(0.105)
Individual heterogeneity:									
M_intensity_t-1	**0.335*****	**0.181****	**0.254*****	**0.349*****	**0.173****	**0.260*****	**0.317*****	**0.183****	**0.222****
	(0.087)	(0.076)	(0.090)	(0.087)	(0.076)	(0.091)	(0.086)	(0.075)	(0.089)
M_high	**0.144****	**0.162*****	-0.107	**0.137****	**0.153*****	-0.081	**0.158*****	**0.138*****	-0.005
	(0.062)	(0.049)	(0.104)	(0.060)	(0.048)	(0.082)	(0.056)	(0.045)	(0.061)
M_medium	**0.199****	0.034	**0.179****	**0.244****	0.125	0.151	**0.298***	**0.305****	-0.002
	(0.090)	(0.076)	(0.090)	(0.113)	(0.095)	(0.112)	(0.180)	(0.145)	(0.177)
M_low	**0.525***	0.124	0.435	**0.428****	-0.114	**0.477*****	0.289	-0.195	0.356
	(0.316)	(0.275)	(0.313)	(0.175)	(0.154)	(0.178)	(0.214)	(0.192)	(0.220)
Constant	**0.262*****	**0.416*****	**0.218*****	**0.260*****	**0.416*****	**0.216*****	**0.259*****	**0.416*****	**0.216*****
	(0.068)	(0.062)	(0.067)	(0.068)	(0.062)	(0.067)	(0.068)	(0.062)	(0.067)
Observations	4,238	4,238	4,238	4,238	4,238	4,238	4,238	4,238	4,238
Log-Likelihood	-702.7	-513.2	-930.9	-702.5	-507.6	-928.9	-703.5	-511.9	-933.6
Rho	0.530	0.531	0.448	0.529	0.533	0.445	0.530	0.530	0.448
LR-rho	**687.4*****	**505.9*****	**472.9*****	**682.1*****	**508.9*****	**466.7*****	**683.6*****	**503.1*****	**470.9*****
Dummies:									
Time (chi2):	**34.18*****	9.300	**30.32*****	**34.75*****	**9.650***	**30.30*****	**35.14*****	8.760	**30.67*****
Mean value (chi2):	**14.10****	6.180	**15.42****	**14.10****	6.450	**15.11****	**14.31****	6.490	**15.29****
Industry (chi2):	**29.82***	18.56	**28.49**	**30.01***	18.14	**29.19***	**30.20***	18.66	**28.87***
Mean value (chi2):	**41.03*****	28.47	**29.31***	**41.45*****	28.45	**29.54***	**40.91*****	28.63	**28.90***

Source: Destatis and MIP; authors' own calculation.

Note: *** p<0.01, ** p<0.05, * p<0.1; standard errors – in parentheses – are clustered at the firm level; for full information on estimation results see Table 3.A.3 in the Appendix.

However, the positive effects regarding the sales share of new products are less significant as compared with the estimates of the FE estimations. With respect to the counter-cyclical adjustment effect, we obtain similar results as well. The GDP-based low growth estimate and even more surprising one of the industry-based low growth estimates show a positive and significant effect. This strengthens the finding that a counter-cyclical innovation adjustment of the product innovators can be a promising strategy to increase their post-crisis product innovation success. The specific industry-level estimate is weakly significant whereas the GDP-based coefficient is even more significant than in Table 3.2. According to the results of the robustness check we would also find support for our hypotheses H1 and H2.

Both tables, Table 3.2 and Table 3.3, support our expectation that a counter-cyclical innovation investment is effective in terms of product innovation success and that it is an even more effective strategy than pro-cyclical innovation investment. However, the ability of firms to adjust their innovation investment depends on their own cash-flow and on their ability to raise external capital, respectively. The funding of innovation activities becomes particularly difficult during recession periods. This could mean that our findings can basically be attributed to firms having a good financial standing. Hence, firms having a weak financial position may typically not be able to make large additional innovation investment, which would not lead to higher innovation success. In a similar line of reasoning, firms having higher innovation success should be typically more able to raise external capital, which would potentially lead to a higher innovation performance, again. To at least partly account for this problem, we split our sample into firms having a mediocre or worse financial standing (*Rating* >= 2.5) and firms having a good or better financial standing (*Rating* < 2.5). The former group refers to financially constrained firms, while the latter group refers to non-financially constrained firms. Table 3.4 shows the regression results on a sample split between financially and non-financially constrained firms.

Table 3.4 supports our findings of Table 3.2 and Table 3.3 for the financially unconstrained firms but not for the financially constrained firms. With respect to the latter group, additional innovation investment hardly leads to a higher sales share of product innovations, even though the estimates are largely positive. With respect to the unconstrained firms, i.e. those that typically have sufficient financial strength to conduct the innovation projects, we find that counter-cyclical innovation investment has a positive effect on the sales share of new products in general and market novelties in particular. Furthermore, the estimates indicate that this counter-cyclical effect is even stronger than the pro-cyclical effect at least for the GDP-based indicators, even though the estimate is not significant.

Table 3.4: Split sample of firms being financially constrained and firms that are not, FE model

	Financially constrained						Financially not constrained					
Thresholds:	**25%; 75% (industry-based)**			**GDP-growth**			**25%; 75% (industry-based)**			**GDP-growth**		
Sales share of:	New	Market	Imit	New	Market	Imit	New	Market	Imit	New	Market	Imit
Intensity_t-1	-0.070	-0.091	0.021	-0.080	-0.092	0.012	0.084	**0.147***	-0.063	0.075	0.116	-0.042
	(0.129)	(0.103)	(0.124)	(0.118)	(0.102)	(0.122)	(0.104)	(0.076)	(0.098)	(0.098)	(0.072)	(0.091)
D_intensity_t|t-1 in periods of:												
High_growth	-0.074	0.174	**-0.247***	-0.086	0.044	-0.130	0.135	**0.214****	-0.079	**0.136****	**0.088****	0.047
	(0.149)	(0.108)	(0.139)	(0.086)	(0.085)	(0.097)	(0.113)	(0.097)	(0.064)	(0.059)	(0.044)	(0.051)
Medium_growth	-0.036	0.035	-0.071	0.033	**0.176****	-0.143	**0.120****	**0.083****	0.037	**0.119***	**0.122****	-0.003
	(0.106)	(0.062)	(0.114)	(0.191)	(0.075)	(0.225)	(0.051)	(0.035)	(0.040)	(0.066)	(0.057)	(0.038)
Low_growth	0.053	0.034	0.019	0.128	0.064	0.064	0.096	**0.149****	-0.053	0.009	0.149	-0.140
	(0.149)	(0.112)	(0.169)	(0.157)	(0.125)	(0.152)	(0.131)	(0.072)	(0.136)	(0.141)	(0.097)	(0.141)
Constant	-0.171	**0.458*****	**-0.629****	-0.166	**0.456*****	**-0.622****	**0.895*****	**0.283*****	**0.612*****	**0.890*****	**0.290*****	**0.600*****
	(0.301)	(0.172)	(0.279)	(0.301)	(0.168)	(0.280)	(0.168)	(0.102)	(0.157)	(0.168)	(0.105)	(0.155)
Observations	824	824	824	824	824	824	3,414	3,414	3,414	3,414	3,414	3,414
Rho	0.991	0.847	0.989	0.991	0.860	0.988	0.925	0.886	0.918	0.925	0.888	0.916
Time dummies (F):	**8.470*****	0.480	**8.800*****	**8.720*****	0.490	**9.620*****	**4.080*****	1.970	**2.550****	**4.000*****	1.620	**2.590*****
Industry dummies (F):	**30.21**	**25.35**	**20.08**	**35.43*****	**18.80*****	**22.91*****	**72.89*****	**26.62*****	**54.39*****	**83.22*****	**27.14*****	**62.16*****

Source: Destatis and MIP; authors' own calculation.

Note: *** $p<0.01$, ** $p<0.05$, * $p<0.1$; standard errors – in parentheses – are clustered at the firm level; for space reasons, we left out the results for the industry-based interaction terms having thresholds at 10% and 90%; for full information on estimation results see Table 3.A.4 in the Appendix.

3.5 Conclusion

This chapter analyses the performance effects of a positive adjustment of product innovators' innovation investment during three different growth periods, i.e. high growth, medium growth and low growth. Our main target is to investigate whether or not a counter-cyclical innovation investment, i.e. an increase of innovation expenses during the crisis, has been an effective strategy for product innovators in terms of post-crisis product innovation success. For these purposes, we use firm-level panel data from Germany that covers the period of 2006-2012, which includes pre-crisis (2006-2007), crisis (2008-2009) and post-crisis (2010-2012) years. To measure the three different growth periods, we use Germany's GDP growth and construct three binary dummy variables. However, the identification of a crisis may be too noisy if it is measured according to an economy-wide indicator as, for instance, GDP growth. In this sense, it could be that firms' innovation success rather substantially depends on the situation in its focal industry, i.e. its primary sales market. For this reason, we also estimate the performance effects of pro- and counter-cyclical innovation investment in the case the growth period dummies are measured by industry-level sales growth rates. To investigate the efficacy of pro- and counter-cyclical innovation adjustment, we interact the indicator measuring an increase in innovation investment with the three different sets of the growth period dummies.

Our research provides several new insights. First, we show that an increase of innovation investment during high and medium growth periods is an effective way for product innovators to increase the innovation success (as measured by the sales share of product innovations). This relationship holds for the industry-based as well as for the GDP-based interaction terms. Whereas the related literature largely focusses on the pro-cyclicality of innovation input and output (see e.g. Wälde and Woitek, 2004; Barlevy, 2007; Fabrizio and Tsolmon, 2014), our results provide first evidence as to the efficacy of a pro-cyclical innovation investment. Second, we find that a counter-cyclical innovation investment seems to be a promising strategy for product innovators as well. Hence, we show that the counter-cyclical innovation investment predicted and found, respectively, by e.g. Bean (1990), Aghion and Saint-Paul (1998), and Aghion et al. (2012) has a positive effect on the product innovators' success. We even find this positive effect to be higher than the performance effect related to a pro-cyclical innovation investment. This implies that a greater investment on product innovations during a crisis has a higher potential to exploit new opportunities and to strengthen the competitive position compared to greater investment during positive growth periods. However, this positive adjustment effect during a crisis only appears to be (strongly) significant in the case the growth periods are measured on the national and not on the industry level. Hence, in case the innovators' focal industry suffers from dropping sales levels increasing innovation expenses do not significantly increase the post-crisis innovation performance. The discrepancy between the findings for industry-based and GDP-based counter-cyclical effects may be due the different perspectives (industry vs. national). Whereas the industry level represents the firms' primary sales market, GDP growth additionally considers changes in labour, capital and supply markets. Therefore, a crisis measured by economy-wide GDP growth incorporates diminished opportunity costs, for instance, on the whole labour market and raw material market. This may lead to greater investment in innovation as compared with the situation where the innovators' focal industry contracts. Finally, we observe that a positive adjustment of innovation investment has only a positive and significant effect on the sales share of market novelties and not on the share of product imitation sales. This relationship holds for the high and medium growth periods and for the low growth period only for GDP-based interaction terms. This implies that those product innovators could gain from greater innovation investment that related these positive adjustments to the development and implementation of more risky and sophisticated products.

Our study has several limitations. First, we analyse the effects of a positive adjustment of innovation investment on innovation performance in the following year. Many innovations, particularly the more radical ones, produce high returns only some years after market introduction. However, our study aims at the short-term effects directly accruing from a significant and short economic crisis that is followed by a strong upturn period as was the case in Germany 2009/2010. We would need panel data of different crisis periods (of different countries) to compare how an increasing innovation investment during a crisis affects firms' innovation performance with our findings. This would allow us to make general conclusions. It remains open for future research. Second, we cannot disentangle the different supply and demand channels underlying the relationship between increasing innovation expenses and increasing product innovation success. Third, our data do not include the information about what type of product innovation the firms spend money on. We only know how much the firms spend in general for innovation. Fourth, even though we do not expect our estimates to suffer from substantial endogeneity biases (see Section 3.3.2), we are still cautious in interpreting our results as causal effects. Fifth, we restrict our estimations to firms that conduct product innovation activities. Therefore, our results are not generalisable but only can be interpreted and evaluated in the context of product innovators. Future research may analyse the adjustment effects on innovation performance across different kinds of firms and may also consider process innovation success as, for instance, the average cost reduction of process innovations.

Despite these limitations, our study has several relevant implications for policymakers. The literature on public R&D subsidies largely finds positive average treatment effects, (see Zúñiga-Vicente et al., 2014), i.e. higher R&D spending due to subsidisation. In combination with our results, R&D subsidies may be an effective way to promote the development and implementation of successful new products. However, this may only hold for positive growth periods as Hud and Hussinger (2015) find a negative treatment effect of R&D subsidies received by German SMEs during the crisis year 2009. Unless direct financial support does help, policymakers may have to support product innovators by providing infrastructure or tax reliefs during crises times.

3.A Appendix

Table 3.A.1: Variable definitions and basic descriptive statistics

Variables	Description	Mean	Std. dev.
Dependent vars.:			
New	Sales share of new products in year t+1	0.178	0.223
Market	Sales share of market novelties in year t+1	0.043	0.107
Imit	Sales share of product imitations in year t+1	0.135	0.192
Explanatory vars.:			
Intensity_t-1	(Innovation expenses / firm sales) in year t-1	0.081	0.136
D_intensity_t|t-1	(Innovation expenses_t - innovation expenses_t-1) / firm sales_t-1	0.009	0.132
Threshold: 10%; 90% (industry-based)			
High_growth	Value of D_intensity_t|t-1 in high growth periods between t & t-1	0.001	0.030
Medium_growth	Value of D_intensity_t|t-1 in medium growth periods between t & t-1	0.008	0.125
Low_growth	Value of D_intensity_t|t-1 in low growth periods between t & t-1	0.000	0.032
Threshold: 25%; 75% (industry-based)			
High_growth	Value of D_intensity_t|t-1 in high growth periods between t & t-1	0.003	0.055
Medium_growth	Value of D_intensity_t|t-1 in medium growth periods between t & t-1	0.006	0.096
Low_growth	Value of D_intensity_t|t-1 in low growth periods between t & t-1	0.000	0.073
Threshold: GDP-growth			
High_growth	Value of D_intensity_t|t-1 in high growth periods between t & t-1	0.008	0.097
Medium_growth	Value of D_intensity_t|t-1 in medium growth periods between t & t-1	0.001	0.062
Low_growth	Value of D_intensity_t|t-1 in low growth periods between t & t-1	0.000	0.065
Controls:			
Sales_growth	(Firm sales_t - firm sales_t-1) / firm sales_t-1	0.089	0.370
Rating	Creditreform's credit rating indicator ranging from 1 (excellent) to 6 (dismal) in t	2.150	0.606
Capital_intensity	Ratio of investment in tangible assets over employees in t	0.120	0.430
Age	Firm age (in years) in t	38.171	42.704
Group	The firm has been part of a group in t - (0/1)	0.465	0.499
Pc_innovator	The firm has introduced at least one process innovation between t & t-2 - (0/1)	0.590	0.492
R&D	The firm has conducted R&D on an occasional or continuous base in t - (0/1)	0.773	0.419
Export	The firm has been an exporter in t - (0/1)	0.740	0.439
Employee dummies:			
1: < 20	The firm employed less than 20 employees in t - (0/1)	0.231	0.421
2: > 19 & < 100	The firm employed between 20 and 99 employees in t - (0/1)	0.297	0.457
3: > 99 & < 250	The firm employed between 100 and 249 employees in t - (0/1)	0.138	0.345
4: > 249 & < 500	The firm employed between 250 and 499 employees in t - (0/1)	0.081	0.273
5: > 499	The firm employed at least 500 employees in t - (0/1)	0.254	0.435
Individual heterogeneity:			
M_intensity_t-1	Mean value of Intensity_t-1	0.081	0.120
M_d_intensity_t|t-1	Mean value of D_intensity_t|t-1	0.006	0.093
Threshold: 10%; 90%			
M_high	Mean value of High_growth	0.002	0.071
M_medium	Mean value of Medium_growth	0.005	0.062
M_low	Mean value of Low_growth	-0.001	0.017
Threshold: 25%; 75%			
M_high	Mean value of High_growth	0.003	0.075
M_medium	Mean value of Medium_growth	0.004	0.049
M_low	Mean value of Low_growth	-0.001	0.037
Threshold: GDP-growth			

M_high	Mean value of High_growth	0.006	0.086
M_medium	Mean value of Medium_growth	0.000	0.032
M_low	Mean value of Low_growth	-0.001	0.033
M_sales_growth	Mean value of Sales_growth	0.088	0.183
M_rating	Mean value of Rating	2.154	0.576
M_capital_intensity	Mean value of Capital_intensity	0.119	0.416
M_age	Mean value of Age	38.226	42.697
M_group	Mean value of Group	0.466	0.470
M_pc_innovator	Mean value of Pc_innovator	0.563	0.376
M_R&D	Mean value of R&D	0.730	0.363
M_export	Mean value of Export	0.736	0.415
1: < 20	Mean value of employee dummy 1	0.229	0.407
2: > 19 & < 100	Mean value of employee dummy 2	0.299	0.436
3: > 99 & < 250	Mean value of employee dummy 3	0.137	0.324
4: > 249 & < 500	Mean value of employee dummy 4	0.081	0.254
5: > 499	Mean value of employee dummy 5	0.254	0.430

Source: Destatis and MIP; authors' own calculation.
Note: Number of observations: 4,238; for convenience, we left out the information about age squared and about the industry dummies.

Table 3.A.2: Full table of Table 3.2

Thresholds:	**10%; 90% (industry-based)**			**25%; 75% (industry-based)**			**GDP growth**		
Sales share of:	New	Market	Imit	New	Market	Imit	New	Market	Imit
Intensity_t-1	0.041	0.027	0.014	0.053	0.045	0.008	0.059	0.036	0.022
	(0.066)	(0.059)	(0.064)	(0.067)	(0.067)	(0.068)	(0.066)	(0.062)	(0.064)
D_intensity_t|t-1 in periods of:									
High_growth	0.020	0.092	-0.072	0.115	**0.188****	-0.073	**0.104***	**0.084****	0.020
	(0.076)	(0.061)	(0.069)	(0.086)	(0.080)	(0.061)	(0.053)	(0.036)	(0.046)
Medium_growth	**0.121*****	**0.098*****	0.023	**0.109****	**0.074****	0.035	**0.112***	**0.108****	0.003
	(0.046)	(0.029)	(0.037)	(0.046)	(0.030)	(0.035)	(0.064)	(0.053)	(0.036)
Low_growth	0.024	0.051	-0.027	0.113	0.094	0.018	0.159	**0.131***	0.028
	(0.109)	(0.069)	(0.117)	(0.095)	(0.063)	(0.103)	(0.112)	(0.075)	(0.109)
Controls:									
Sales_growth	-0.013	-0.007	-0.006	-0.014	-0.007	-0.007	-0.014	-0.007	-0.006
	(0.011)	(0.006)	(0.010)	(0.012)	(0.007)	(0.010)	(0.011)	(0.006)	(0.010)
Rating	0.006	0.004	0.001	0.006	0.004	0.002	0.006	0.004	0.001
	(0.020)	(0.008)	(0.018)	(0.020)	(0.008)	(0.018)	(0.020)	(0.008)	(0.018)
Capital_intensity	0.026	0.027	-0.001	0.026	0.026	-0.000	0.026	0.026	-0.001
	(0.028)	(0.018)	(0.013)	(0.028)	(0.018)	(0.013)	(0.028)	(0.018)	(0.013)
Age	**0.018*****	**-0.006****	**0.012*****	**0.018*****	**-0.006****	**0.013*****	**0.018*****	**-0.006****	**0.012*****
	(0.004)	(0.003)	(0.004)	(0.004)	(0.003)	(0.004)	(0.004)	(0.003)	(0.004)
Age2	**0.000****	**0.000*****	0.000	**0.000****	**0.000*****	0.000	**0.000****	**0.000*****	0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Group	-0.016	0.003	-0.019	-0.015	0.004	-0.019	-0.015	0.003	-0.018
	(0.018)	(0.009)	(0.016)	(0.018)	(0.009)	(0.016)	(0.018)	(0.009)	(0.016)
Pc_innovator	-0.010	-0.004	-0.006	-0.010	-0.003	-0.006	-0.010	-0.004	-0.006
	(0.010)	(0.005)	(0.010)	(0.010)	(0.005)	(0.010)	(0.010)	(0.005)	(0.010)
R&D	0.012	0.005	0.007	0.013	0.005	0.007	0.013	0.005	0.008
	(0.012)	(0.005)	(0.012)	(0.012)	(0.005)	(0.012)	(0.012)	(0.005)	(0.012)
Export	0.004	0.015	-0.010	0.005	0.016	-0.011	0.005	0.015	-0.010
	(0.022)	(0.010)	(0.021)	(0.022)	(0.010)	(0.021)	(0.022)	(0.010)	(0.021)
Employee dummies:									
1: < 20	0.002	-0.016	0.018	0.001	-0.015	0.016	0.001	-0.017	0.018
	(0.104)	(0.073)	(0.082)	(0.104)	(0.073)	(0.081)	(0.104)	(0.073)	(0.082)
2: > 19 & < 100	0.042	-0.034	0.076	0.042	-0.032	0.074	0.041	-0.034	0.076
	(0.085)	(0.054)	(0.067)	(0.086)	(0.055)	(0.067)	(0.085)	(0.054)	(0.067)
3: > 99 & < 250	-0.020	-0.041	0.022	-0.019	-0.041	0.022	-0.020	-0.041	0.022
	(0.074)	(0.051)	(0.056)	(0.074)	(0.051)	(0.056)	(0.074)	(0.051)	(0.056)
4: > 249 & < 500	0.013	0.014	-0.001	0.013	0.014	-0.001	0.013	0.013	-0.001
	(0.063)	(0.038)	(0.047)	(0.062)	(0.037)	(0.047)	(0.062)	(0.038)	(0.047)
Constant	**0.581*****	0.078	**0.503*****	**0.580*****	0.069	**0.511*****	**0.581*****	0.077	**0.503*****
	(0.178)	(0.088)	(0.173)	(0.179)	(0.089)	(0.174)	(0.178)	(0.089)	(0.174)
Observations	4,238	4,238	4,238	4,238	4,238	4,238	4,238	4,238	4,238
Rho	0.912	0.836	0.903	0.913	0.837	0.905	0.913	0.835	0.904
Dummies:									
Time (F):	**9.640*****	0.960	**8.910*****	**9.910*****	1.130	**8.750*****	**10.04*****	0.980	**8.950*****
Industry (F):	**75.77*****	**25.47*****	**64.72*****	**66.89*****	**25.16*****	**56.65*****	**74.45*****	**25.14*****	**63.13*****

Source: Destatis and MIP; authors' own calculation.

Note: *** p<0.01, ** p<0.05, * p<0.1; standard errors – in parentheses – are clustered at the firm level.

Table 3.A.3: Full table of Table 3.3

Thresholds:	10%; 90% (industry-based)			25%; 75% (industry-based)			GDP growth		
Sales share of:	New	Market	Imit	New	Market	Imit	New	Market	Imit
Intensity_t-1	0.029	0.051	-0.008	0.013	0.066	-0.026	0.042	0.041	0.023
	(0.070)	(0.062)	(0.075)	(0.071)	(0.063)	(0.077)	(0.069)	(0.061)	(0.074)
D_intensity_t|t-1 in periods of:									
High_growth	-0.038	**0.249****	-0.118	0.073	**0.300*****	-0.090	0.057	**0.101*****	0.009
	(0.108)	(0.124)	(0.114)	(0.070)	(0.064)	(0.076)	(0.045)	(0.039)	(0.048)
Medium_growth	**0.072***	**0.117*****	-0.015	0.065	**0.083****	0.000	0.094	**0.127*****	-0.010
	(0.041)	(0.035)	(0.044)	(0.044)	(0.038)	(0.047)	(0.059)	(0.049)	(0.064)
Low_growth	-0.052	0.180	-0.125	-0.047	**0.144***	-0.118	0.028	**0.190****	-0.058
	(0.126)	(0.116)	(0.135)	(0.083)	(0.075)	(0.088)	(0.099)	(0.092)	(0.105)
Controls:									
Sales_growth	-0.005	-0.016	0.005	-0.005	-0.014	0.005	-0.005	-0.015	0.004
	(0.012)	(0.011)	(0.013)	(0.012)	(0.011)	(0.012)	(0.012)	(0.011)	(0.013)
Rating	0.014	0.017	0.005	0.014	0.016	0.006	0.014	0.017	0.005
	(0.018)	(0.017)	(0.020)	(0.018)	(0.017)	(0.020)	(0.018)	(0.017)	(0.020)
Capital_intensity	0.045	0.041	0.015	0.045	0.039	0.016	0.044	0.040	0.015
	(0.032)	(0.029)	(0.034)	(0.032)	(0.029)	(0.034)	(0.032)	(0.029)	(0.034)
Age	0.062	-0.467	0.643	0.087	-0.434	0.649	0.055	-0.418	0.596
	(0.688)	(0.558)	(0.705)	(0.688)	(0.559)	(0.704)	(0.687)	(0.558)	(0.702)
Age2	**0.000***	**0.000****	0.000	**0.000***	**0.000****	0.000	**0.000***	**0.000****	0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Group	-0.015	0.021	-0.026	-0.014	0.023	-0.026	-0.015	0.022	-0.026
	(0.021)	(0.020)	(0.023)	(0.021)	(0.020)	(0.023)	(0.021)	(0.020)	(0.023)
Pc_innovator	**-0.020****	**-0.018***	-0.012	**-0.020****	**-0.018***	-0.011	**-0.020****	**-0.018***	-0.011
	(0.010)	(0.010)	(0.011)	(0.010)	(0.010)	(0.011)	(0.010)	(0.010)	(0.011)
R&D	**-0.034****	-0.019	**-0.038****	**-0.034****	-0.017	**-0.039****	**-0.034****	-0.018	**-0.039****
	(0.015)	(0.015)	(0.015)	(0.015)	(0.015)	(0.015)	(0.015)	(0.015)	(0.015)
Export	0.007	0.012	-0.007	0.006	0.014	-0.008	0.007	0.011	-0.006
	(0.025)	(0.025)	(0.026)	(0.025)	(0.025)	(0.026)	(0.025)	(0.025)	(0.026)
Employee dummies:									
1: < 20	-0.050	-0.034	-0.030	-0.049	-0.032	-0.029	-0.049	-0.037	-0.028
	(0.088)	(0.081)	(0.095)	(0.088)	(0.081)	(0.095)	(0.088)	(0.081)	(0.095)
2: > 19 & < 100	0.017	-0.086	0.081	0.017	-0.082	0.081	0.017	-0.086	0.082
	(0.080)	(0.074)	(0.086)	(0.080)	(0.073)	(0.086)	(0.080)	(0.074)	(0.086)
3: > 99 & < 250	-0.026	-0.103	0.042	-0.026	-0.103	0.042	-0.025	-0.104	0.043
	(0.070)	(0.066)	(0.076)	(0.070)	(0.066)	(0.076)	(0.070)	(0.066)	(0.076)
4: > 249 & < 500	0.014	0.005	0.012	0.014	0.005	0.012	0.015	0.004	0.013
	(0.047)	(0.046)	(0.050)	(0.047)	(0.046)	(0.050)	(0.047)	(0.046)	(0.050)
Individual heterogeneity:									
M_intensity_t-1	**0.335*****	**0.181****	**0.254*****	**0.349*****	**0.173****	**0.260*****	**0.317*****	**0.183****	**0.222****
	(0.087)	(0.076)	(0.090)	(0.087)	(0.076)	(0.091)	(0.086)	(0.075)	(0.089)
M_high	**0.144****	**0.162*****	-0.107	**0.137****	**0.153*****	-0.081	**0.158*****	**0.138*****	-0.005
	(0.062)	(0.049)	(0.104)	(0.060)	(0.048)	(0.082)	(0.056)	(0.045)	(0.061)
M_medium	**0.199****	0.034	**0.179****	**0.244****	0.125	0.151	**0.298***	**0.305****	-0.002
	(0.090)	(0.076)	(0.090)	(0.113)	(0.095)	(0.112)	(0.180)	(0.145)	(0.177)
M_low	**0.525***	0.124	0.435	**0.428****	-0.114	**0.477*****	0.289	-0.195	0.356
	(0.316)	(0.275)	(0.313)	(0.175)	(0.154)	(0.178)	(0.214)	(0.192)	(0.220)
M_sales_growth	0.002	0.043	-0.014	0.001	0.041	-0.017	0.000	**0.046***	-0.020
	(0.032)	(0.028)	(0.032)	(0.032)	(0.028)	(0.032)	(0.032)	(0.028)	(0.032)

M_rating	-0.017	-0.008	-0.008	-0.017	-0.007	-0.009	-0.017	-0.010	-0.007
	(0.021)	(0.019)	(0.022)	(0.021)	(0.019)	(0.022)	(0.021)	(0.019)	(0.022)
M_capital_intensity	**-0.080****	-0.047	-0.062	**-0.081****	-0.046	-0.064	**-0.081****	-0.047	-0.063
	(0.039)	(0.033)	(0.041)	(0.039)	(0.033)	(0.041)	(0.039)	(0.033)	(0.041)
M_age	-0.063	0.466	-0.643	-0.087	0.433	-0.649	-0.056	0.418	-0.596
	(0.688)	(0.558)	(0.705)	(0.688)	(0.559)	(0.704)	(0.687)	(0.558)	(0.702)
M_age2	**-0.000***	**-0.000****	-0.000	**-0.000***	**-0.000****	-0.000	**-0.000***	**-0.000****	-0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
M_group	0.015	-0.031	0.022	0.013	-0.034	0.023	0.013	-0.032	0.022
	(0.027)	(0.024)	(0.028)	(0.027)	(0.024)	(0.027)	(0.027)	(0.024)	(0.028)
M_pc_innovator	**0.156*****	**0.096*****	**0.125*****	**0.156*****	**0.095*****	**0.126*****	**0.157*****	**0.096*****	**0.126*****
	(0.019)	(0.017)	(0.019)	(0.019)	(0.017)	(0.019)	(0.019)	(0.017)	(0.019)
M_R&D	**0.187*****	**0.188*****	**0.148*****	**0.186*****	**0.185*****	**0.149*****	**0.187*****	**0.186*****	**0.150*****
	(0.023)	(0.023)	(0.023)	(0.023)	(0.023)	(0.023)	(0.023)	(0.023)	(0.023)
M_export	0.056*	0.051*	0.052*	0.057*	0.049*	0.054*	0.055*	0.052*	0.052*
	(0.030)	(0.030)	(0.031)	(0.030)	(0.030)	(0.031)	(0.030)	(0.030)	(0.031)
M_empl. dummies:									
1: < 20	0.099	0.029	0.054	0.099	0.025	0.055	0.100	0.033	0.051
	(0.091)	(0.084)	(0.098)	(0.091)	(0.084)	(0.098)	(0.091)	(0.084)	(0.098)
2: > 19 & < 100	-0.006	0.053	-0.076	-0.006	0.048	-0.075	-0.007	0.053	-0.078
	(0.083)	(0.076)	(0.089)	(0.083)	(0.076)	(0.089)	(0.083)	(0.076)	(0.089)
3: > 99 & < 250	0.062	0.100	-0.013	0.062	0.100	-0.013	0.061	0.101	-0.014
	(0.074)	(0.068)	(0.079)	(0.074)	(0.068)	(0.079)	(0.074)	(0.068)	(0.079)
4: > 249 & < 500	-0.028	-0.053	-0.018	-0.028	-0.052	-0.019	-0.028	-0.052	-0.019
	(0.054)	(0.051)	(0.056)	(0.054)	(0.051)	(0.056)	(0.054)	(0.051)	(0.056)
Constant	**0.262*****	**0.416*****	**0.218*****	**0.260*****	**0.416*****	**0.216*****	**0.259*****	**0.416*****	**0.216*****
	(0.068)	(0.062)	(0.067)	(0.068)	(0.062)	(0.067)	(0.068)	(0.062)	(0.067)
Observations	4,238	4,238	4,238	4,238	4,238	4,238	4,238	4,238	4,238
Log-Likelihood	-702.7	-513.2	-930.9	-702.5	-507.6	-928.9	-703.5	-511.9	-933.6
Rho	0.530	0.531	0.448	0.529	0.533	0.445	0.530	0.530	0.448
LR-rho	**687.4*****	**505.9*****	**472.9*****	**682.1*****	**508.9*****	**466.7*****	**683.6*****	**503.1*****	**470.9*****
Dummies									
Time (chi2):	**34.18*****	9.300	**30.32*****	**34.75*****	**9.650***	**30.30*****	**35.14*****	8.760	**30.67*****
Mean value (chi2):	**14.10****	6.180	**15.42****	**14.10****	6.450	**15.11****	**14.31****	6.490	**15.29****
Industry (chi2):	**29.82***	18.56	**28.49**	**30.01***	18.14	**29.19***	**30.20***	18.66	**28.87***
Mean value (chi2):	**41.03*****	28.47	**29.31***	**41.45*****	28.45	**29.54***	**40.91*****	28.63	**28.90***

Source: Destatis and MIP; authors' own calculation.

Note: *** p<0.01, ** p<0.05, * p<0.1; standard errors – in parentheses – are clustered at the firm level.

Table 3.A.4: Full table of Table 3.4

	Financially constrained						Financially not constrained					
Thresholds:	25%; 75% (industry-based)			GDP-growth			25%; 75% (industry-based)			GDP-growth		
Sales share of:	New	Market	Imit	New	Market	Imit	New	Market	Imit	New	Market	Imit
Intensity_t-1	-0.070	-0.091	0.021	-0.080	-0.092	0.012	0.084	**0.147***	-0.063	0.075	0.116	-0.042
	(0.129)	(0.103)	(0.124)	(0.118)	(0.102)	(0.122)	(0.104)	(0.076)	(0.098)	(0.098)	(0.072)	(0.091)
D_intensity_t|t-1 in periods of:												
High_growth	-0.074	0.174	**-0.247***	-0.086	0.044	-0.130	0.135	**0.214****	-0.079	**0.136****	**0.088****	0.047
	(0.149)	(0.108)	(0.139)	(0.086)	(0.085)	(0.097)	(0.113)	(0.097)	(0.064)	(0.059)	(0.044)	(0.051)
Medium_growth	-0.036	0.035	-0.071	0.033	**0.176****	-0.143	**0.120****	**0.083****	0.037	**0.119***	**0.122****	-0.003
	(0.106)	(0.062)	(0.114)	(0.191)	(0.075)	(0.225)	(0.051)	(0.035)	(0.040)	(0.066)	(0.057)	(0.038)
Low_growth	0.053	0.034	0.019	0.128	0.064	0.064	0.096	**0.149****	-0.053	0.009	0.149	-0.140
	(0.149)	(0.112)	(0.169)	(0.157)	(0.125)	(0.152)	(0.131)	(0.072)	(0.136)	(0.141)	(0.097)	(0.141)
Controls:												
Sales_growth	-0.009	0.004	-0.012	-0.008	0.005	-0.014	-0.012	-0.007	-0.005	-0.013	-0.007	-0.006
	(0.036)	(0.024)	(0.034)	(0.036)	(0.024)	(0.035)	(0.011)	(0.007)	(0.010)	(0.011)	(0.006)	(0.010)
Capital_intensity	-0.081	0.001	-0.082	-0.074	-0.000	-0.074	0.001	0.002	-0.000	0.002	0.002	-0.000
	(0.077)	(0.019)	(0.073)	(0.072)	(0.020)	(0.066)	(0.016)	(0.007)	(0.013)	(0.016)	(0.008)	(0.013)
Age	0.003	-0.010	0.013	0.003	-0.009	0.012	**0.020*****	**-0.006****	**0.014*****	**0.020*****	**-0.006****	**0.014*****
	(0.012)	(0.007)	(0.011)	(0.012)	(0.006)	(0.011)	(0.004)	(0.003)	(0.004)	(0.004)	(0.003)	(0.004)
Age2	**-0.000****	0.000	**-0.000****	**-0.000****	0.000	**-0.000****	**0.000****	**0.000****	0.000	**0.000****	**0.000****	0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Group	-0.046	0.002	-0.049	-0.045	0.000	-0.046	-0.017	-0.001	-0.016	-0.017	-0.001	-0.016
	(0.040)	(0.029)	(0.033)	(0.041)	(0.030)	(0.035)	(0.020)	(0.009)	(0.018)	(0.020)	(0.009)	(0.018)
Pc_innovator	**-0.069****	-0.008	**-0.061****	**-0.068****	-0.007	**-0.061****	-0.000	0.000	-0.000	-0.000	-0.000	0.000
	(0.028)	(0.012)	(0.030)	(0.028)	(0.012)	(0.029)	(0.010)	(0.005)	(0.010)	(0.010)	(0.005)	(0.010)
R&D	0.039	-0.002	0.041	0.038	-0.005	0.042	0.012	0.005	0.007	0.012	0.005	0.007
	(0.031)	(0.014)	(0.032)	(0.031)	(0.013)	(0.033)	(0.013)	(0.005)	(0.013)	(0.013)	(0.005)	(0.013)
Export	-0.017	-0.007	-0.010	-0.022	-0.009	-0.013	-0.009	0.009	-0.018	-0.010	0.009	-0.019
	(0.035)	(0.024)	(0.038)	(0.033)	(0.025)	(0.036)	(0.022)	(0.008)	(0.023)	(0.022)	(0.007)	(0.024)
Employee dummies:												
1: < 20	**1.047*****	-0.041	**1.087*****	**1.052*****	-0.036	**1.088*****	-0.128	-0.033	-0.095	-0.128	-0.035	-0.094
	(0.211)	(0.142)	(0.172)	(0.211)	(0.141)	(0.176)	(0.105)	(0.081)	(0.068)	(0.105)	(0.080)	(0.068)
2: > 19 & < 100	**0.854*****	**-0.192***	**1.045*****	**0.856*****	**-0.187***	**1.043*****	-0.004	0.004	-0.008	-0.004	0.002	-0.006

	(0.195)	(0.099)	(0.147)	(0.196)	(0.098)	(0.151)	(0.081)	(0.049)	(0.055)	(0.081)	(0.049)	(0.055)
3: > 99 & < 250	**0.776*** **	**-0.174***	**0.950*** **	**0.776*** **	**-0.169***	**0.945*** **	-0.056	-0.007	-0.049	-0.056	-0.008	-0.048
	(0.171)	(0.095)	(0.091)	(0.172)	(0.093)	(0.093)	(0.066)	(0.044)	(0.043)	(0.066)	(0.044)	(0.043)
4: > 249 & < 500	**0.803*** **	-0.016	**0.819*** **	**0.804*** **	-0.016	**0.820*** **	-0.024	0.013	-0.037	-0.023	0.013	-0.036
	(0.045)	(0.024)	(0.043)	(0.045)	(0.023)	(0.043)	(0.056)	(0.039)	(0.036)	(0.056)	(0.039)	(0.036)
Constant	-0.171	**0.458*** **	**-0.629** **	-0.166	**0.456*** **	**-0.622** **	**0.895*** **	**0.283*** **	**0.612*** **	**0.890*** **	**0.290*** **	**0.600*** **
	(0.301)	(0.172)	(0.279)	(0.301)	(0.168)	(0.280)	(0.168)	(0.102)	(0.157)	(0.168)	(0.105)	(0.155)
Observations	824	824	824	824	824	824	3,414	3,414	3,414	3,414	3,414	3,414
Rho	0.991	0.847	0.989	0.991	0.860	0.988	0.925	0.886	0.918	0.925	0.888	0.916
Time dummies (F):	**8.470*** **	0.480	**8.800*** **	**8.720*** **	0.490	**9.620*** **	**4.080*** **	1.970	**2.550** **	**4.000*** **	1.620	**2.590*** **
Industry dummies (F):	**30.21**	**25.35**	**20.08**	**35.43*** **	**18.80*** **	**22.91*** **	**72.89*** **	**26.62*** **	**54.39*** **	**83.22*** **	**27.14*** **	**62.16*** **

Source: Destatis and MIP; authors' own calculation.

Note: *** p<0.01, ** p<0.05, * p<0.1; standard errors – in parentheses – are clustered at the firm level; for space reasons, we left out the results for the industry-based interaction terms having thresholds at 10% and 90%.

Chapter 4

Employment Effects of Innovations over the Business Cycle: Firm-Level Evidence from European Countries[32]

4.1 Introduction

The global economic crisis set off in 2008 has been a serious threat to the stability of most economies in the world. More than 5.37 million jobs (-2.4%) were destroyed between 2008 and 2010 just in Europe. The challenge European policymakers face has been to overcome the crisis and to improve long-term competitiveness and to stimulate growth. Research and development (R&D) and innovation activities are typically regarded as efficient instruments to spur firms' competitiveness and, consequently, economic growth and job creation. For this reason, improving the conditions for research and innovation is one of the main objectives of Europe 2020 – EU's large-scale growth strategy implemented in 2010 (EC, 2012). The key issue whether such a strategy can be successful depends on the extent to which EU countries are able to translate new products and technologies into employment growth during a recession.

In this chapter, we analyse the cyclicality of the link between innovation and job creation for a large set of European firms. Our central research question is: How do different types of innovation affect employment growth during different phases of the business cycle? In this sense, is innovation equally employment-creating in all phases of the business cycle or do we observe a pro- or counter-cyclical effect of innovation on employment growth? Investigating employment creation and destruction of innovation over the business cycle, allows us to answer in particular the intriguing research question whether or not economic activities of

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innovators are more resilient to negative economic shocks.[33] The answers largely rely on two different effects. The first effect refers to the dependency of firms' innovation activities on business cycle fluctuations. A growing literature has studied firms' innovation input behaviour over the business cycle and has found that firms expand these activities during economic upturns (see e.g. Barlevy, 2007; Fabrizio and Tsolmon, 2014). The second effect describes the impact of innovation output on firms' employment growth. The literature has shown that this effect depends on several mechanisms in a complex manner. A main conclusion that can be drawn is that the effect is considerably driven not only by the specific type of innovation but also by the demand for firms' products (see Pianta, 2005 for an overview). Product innovations have mainly been found to stimulate firms' labour demand, whereas the effect of process and organisational innovations is ambiguous. Even though the literature stresses that demand-driven effects are crucial for employment consequences of innovation, there is no firm-level study yet investigating the firms' ability to transform innovation into employment growth over the business cycle. We contribute to the literature by providing first evidence regarding firm-level employment growth effects of innovation over different phases of a business cycle.

Our analysis disentangles this complex relationship by using the structural model of Harrison et al. (2014). This model is conceived to examine the labour-creating and labour-destructing effects of innovations. In this respect, the model establishes a theoretical link between firm-level employment growth and innovation output in terms of (i) the sales growth generated by product innovations, i.e. new or improved products, and (ii) the efficiency gains attributable to process innovations, i.e. new or improved processes. We extend the model's standard specification by allowing efficiency improvements to depend on organisational innovations as well. Schumpeter (1934) already emphasised that firms implement new organisational structures from time to time and do not only rely on product and process innovations. Controlling for organisational innovations also allows us to identify the employment growth effects of process innovation more accurately.

To estimate the model, we use data from the Europe-wide Community Innovation Survey (CIS). Our sample covers information on manufacturing firms from 26 European countries and includes more than 200,000 firm-year observations. We observe them for the period from 1998 to 2010, which is reasonably long and allows us to capture potential business cycle effects. The estimations are weighted, i.e. our findings are representative for the manufacturing sectors of the countries covered. To analyse the cyclicality of the employment growth effects of innovation, we use *country-specific* GDP growth rates to create dummy variables dividing the business cycle into four different phases, i.e. upturn, boom, downturn and recession. Furthermore, we study whether or not employment creation and destruction of innovation over the business cycle differs by firm size. Prior empirical evidence has shown that jobs are typically created in small and medium-sized enterprises (SMEs) (see e.g. Neumark et al., 2011).

Our empirical analysis reveals four important findings. First, the net employment growth effect of product innovators is pro-cyclical. It turns out to be positive in all business cycle phases except for the recession. This means, the potential labour-creating effect exceeds the potential labour-destructing effect of product innovations except during recessions. Second, product innovators are more resilient to recessions than firms that have not introduced product innovations (non-product innovators). When facing negative economic growth, product innovators on average cut jobs. However, the level of job destruction is much more modest as compared to the job destruction of non-product innovators. Third, this resilience of product

[33] Regional-industry level evidence points towards this direction. Delgado et al. (2015) found that strong regional clusters in terms of patenting have facilitated employment resilience in the US during the 2007-2009 recession.

innovators is, however, only found in SMEs but not in large firms. Fourth, on average, process and organisational innovations particularly reduce labour demand of firms during upturn and downturn periods. Overall, our results suggest that product innovators are an important driving force for firm-level employment growth. They are particularly important for securing jobs during recessions. In contrast, process and organisational innovations tend to displace employment.

The chapter is structured as follows. The next section reviews the relevant literature and develops the hypotheses, whereas Section 4.3 describes the underlying theoretical model. Section 4.4 explains the empirical implementation by discussing the data, descriptive statistics and the estimation approach. Section 4.5 presents the empirical results. Section 4.6 briefly summarises and concludes.

4.2 Related literature and hypotheses

This section reviews the literature relevant to our analysis and develops hypotheses. First, we present the basic findings on firms' innovation activities and their business cycle dependency. Second, we shortly describe the theory on the employment growth effects of different types of innovation and present the main empirical findings. Third, based on the literature review we develop our hypotheses on the employment effects of innovations over the business cycle.

4.2.1 Innovation activities and the business cycle

The literature on the relationship between the business cycle and innovation has mostly focused on innovation input. During recessions, firms shift more resources to productivity-enhancing activities, such as innovative investment. This counter-cyclical pattern arises because the opportunity costs of long-term innovative investment are lower than short-time capital investment during recessions (see e.g. Bean, 1990; Gali and Hammour, 1991; Aghion and Saint-Paul, 1998). In contrast to these predictions, recent empirical analyses find a pro-cyclical pattern of innovative investment. Some authors attribute this result to the cash-flow dependency of financing innovation activities (see e.g. Himmelberg and Petersen, 1994; Mulkay et al., 2001; Ouyang, 2011). Other authors argue that the investment decision is strategically postponed to high demand periods to maximise the innovations' profitability (see e.g. Barlevy, 2007). Aghion et al. (2010, 2012) find evidence for pro- and counter-cyclicality. Accordingly, pro-cyclicality arises for financially constrained firms, whereas non-constrained firms act counter-cyclically.

In addition, there is some research on the timing of the market introduction and commercialisation of innovations. Shleifer (1986), Francois and Lloyd-Ellis (2003) and Barlevy (2007) develop similar models and argue that the innovators expect imitators to enter after the implementation of innovations.[34] Anticipating this, the innovators postpone the product commercialisation to periods of high demand. Only this allows them to capture most of the profits. By using US-American firm-level data, Fabrizio and Tsolmon's (2014) empirical results support this pro-cyclicality. Furthermore, Axalorglou (2003) uses industry-level data and also finds a positive relationship between growth and the introduction of new products.

[34] In their model, Francois and Lloyd-Ellis (2003) do not build on imitation. Instead, they assume that after the implementation knowledge disseminates to the rivals. This eventually limits the innovators' time as successful incumbents.

4.2.2 Employment effects of innovations

Technological progress may be labour-saving or labour-creating, and may or may not cause a change in the skill composition (see Vivarelli, 2014 for an overview). In this review, we neglect the skill aspect because our data does not include information on skills but only allows us to study employment growth effects of innovations at the firm level.[35]

Theoretical contributions do not provide clear-cut predictions on whether or not innovations create or destroy jobs (see Petit, 1995; Blechinger et al., 1998 for overviews). Identifying the employment growth impact rather requires separating the effects of product from the effects of process innovations. At the firm level, product innovations may affect employment via three channels. First, introducing new products on the market generates new demand and therefore increases labour demand (*direct demand effect of product innovation*). The second channel is related to the relative productivity between new and old products. If new products are produced more (less) efficiently than old products, they will require less (more) input for a given output. This dampens (strengthens) the positive demand effect, thus also employment growth (*productivity effect of product innovation*). The third channel refers to an *indirect demand effect of product innovation*. According to this, new product demand may replace the demand for the innovators' old products to some degree. This "product cannibalisation" reduces labour demand related to the old products. In contrast, the innovators' labour demand will increase if new and old products complement each other. In this case, new product demand stimulates old product demand. Therefore, at the firm level product innovations will only unambiguously increase firms' employment levels if the relationship is complementary. Further employment effects arise at the macro and the sector level.[36] For instance, the increase in new product demand may come at the expense of lower demand for rivals' products (business stealing effect). This reduces the rivals' labour demand. However, product and labour demand of those competitors eventually increase that offer products complementary to the innovators' new products.

Despite ambiguous theoretical predictions, the majority of empirical studies find product innovations to create jobs (see e.g. Entorf and Pohlmeier, 1990; Brouwer et al., 1993; König et al., 1995; Van Reenen, 1997; Smolny, 2002; Garcia et al., 2004; Hall et al., 2008; Peters, 2008; Lachenmaier and Rottmann, 2011; Dachs and Peters, 2014; Harrison et al., 2014). This implies that the employment-inducing effects outweigh the potential employment-reducing effects of product innovations. However, only Garcia et al. (2004), Hall et al. (2008), Peters (2008), Dachs and Peters (2014) and Harrison et al. (2014) explicitly disentangle the labour-creating from the labour-reducing effects of product innovations.

In contrast to product innovations, the direct effect of process innovations is an increase in the innovators' production efficiency (*productivity effect of process innovation*). This type of efficiency gain implies that the same level of output can be produced with less input, e.g. labour. Hence, the productivity effect of process innovation is likely to reduce the innovators' demand for labour. However, as efficiency improvements cause marginal production costs to decline, they open up possibilities for price reductions. Lower prices stimulate the innovators' product demand. In this way, price cuts can alleviate the employment losses related to the productivity effect or even reverse them (*price effect of process innovations*). The magnitude of the price effect is determined by the size of the price reduction, the price elasticity of

[35] Two strands of the literature centre on the impact of innovation on skills: The literature on skill-biased technological change (see e.g. Caroli and Van Reenen, 2001; Acemoglu, 2002; Bresnahan et al., 2002; Piva et al., 2005) and on routine-biased technological change (see e.g. Autor et al., 2003 and Goos et al., 2014).

[36] For empirical research, see e.g. Freeman et al. (1982), Vivarelli and Pianta (2000), Leitner et al. (2011), Pianta and Lucchese (2012) and Damijan et al. (2014).

demand and the competitive environment, in particular competitors' reaction to price reductions.

Empirical results for the effect of process innovations are inconclusive. Mainly based on reduced form regressions, Entorf and Pohlmeier (1990), Van Reenen (1997) and Hall et al. (2008) report no significant effect of process innovations on employment, whereas König et al. (1995) and Lachenmaier and Rottmann (2011) even find that process innovations increase the firms' employment level. Using the same structural approach as this paper, Peters (2008), Dachs and Peters (2014) and Harrison et al. (2014) find evidence for a small negative gross effect of process innovation, i.e. process innovations cut labour due to improved productivity. But the growth of demand for old products – partly provoked by price reductions following the increase in efficiency – is strong enough to compensate for it.

The majority of the employment studies focus on product and process innovations (technological innovations). This is a significant drawback because analysing employment effects of innovations also requires the adoption of a non-technological perspective in the form of organisational innovations (Edquist et al., 2001). Schumpeter (1934) already stated that firms not only implement new products and processes, but also adjust their business practices and reorganise their organisational structures. However, organisational innovations have largely been neglected for some time due to measurement and definition problems (Lam, 2005; Armbruster et al., 2008). OECD and Eurostat (2005) provide the first harmonised definition of organisational innovations and how to measure them in innovation surveys. Evangelista and Vezzani (2011) analyse CIS data of several European countries and descriptively show that there are more organisational innovators than product and process innovators. By using a different data set covering information on a large set of European firms, Tether and Tajar's results (2008) disclose a very similar pattern.

There is no theoretical model explicitly considering employment effects of organisational innovations. However, Ichniowski et al. (1996) review the literature on workplace innovations and performance. They argue that these kinds of innovations should increase productivity, which should lead to lower costs and higher product demand. Indeed, empirical research supports the productivity-enhancing effect of organisational innovations (see e.g. Ichniowski et al., 1997; Black and Lynch, 2004; Gera and Gu, 2004). Like in the case of process innovations, the evidence as to the employment growth effect of organisational innovations is ambiguous as well. Greenan (2003) shows that a shift towards a flexible enterprise increases the firms' job destruction rate. Likewise, Bauer and Bender (2004) find delayering and the transfer of responsibilities to significantly decrease net employment growth rates, whereas team work causes the employment level to increase. Positive employment effects have also been found, for instance, by Falk (2001), Addison et al. (2008) and Evangelista and Vezzani (2011).

4.2.3 Hypotheses: Employment effects of innovations over the business cycle

Based on the related literature presented in Section 4.2.2, it is evident that product demand plays an important role for employment growth effects of technological and non-technological innovations. These demand effects are likely to vary with different phases of a business cycle as do the productivity effects of process and organisational innovations. In this section, we develop a set of hypotheses about the employment growth effects of different types of innovations at different phases of the business cycle.

The gross employment effect of product innovations depends on two effects: (i) the size of the direct demand effect and (ii) the size and direction of the productivity effect. The latter refers to the productivity of new products, i.e. the level of output per unit of input, relative to the productivity of old products. As this is mainly technology-driven, we do not expect the relative productivity to be significantly affected by macroeconomic demand conditions.

Hypothesis H1a: The productivity effect of product innovations is independent of the business cycle.

Instead, we expect the direct demand effect to vary with the business cycle. In line with the literature presented in Section 4.2.1, we assume that innovators are more successful in selling new products during positive growth periods. In this situation, incomes are increasing and budget restrictions are less tight. In contrast, we expect product innovations to have a lower direct demand effect during downturn and recession periods. Furthermore, the utilisation of production capacities is pro-cyclical (see e.g. Corrado and Mattey, 1997; Fagnart et al., 1999). Smolny (2002) finds that higher rates of capacity utilisation stimulate employment growth. Given these two stylised facts, we expect product innovators to be more likely to expand their employment when facing demand increases due to new products in upturn and boom periods as they already produce at high or full capacity. During recessions, product innovations are accordingly expected to have less of an effect on employment because direct demand effects tend to be weaker and firms are already struggling with excess capacity. For these reasons, we expect a pro-cyclical demand effect of product innovation to always be positive.

Hypothesis H1b: The direct demand effect of product innovations is pro-cyclical and always positive.

Hypotheses H1a and H1b capture the gross employment effect of product innovations. To obtain the net employment effect of product innovations, it is further necessary to consider the indirect demand effect. In case of a complementary relationship between the innovators' new and old products, a higher (lower) direct demand effect is also associated with a higher (lower) indirect demand effect. Instead, if new and old products were substitutes, we would expect the demand for old products to disproportionately decline during downturns and recessions compared to upturns and booms. This decline may be reinforced by firms that face pressure to reduce their product range during downturn and recession periods. Bernard et al. (2010), Broda and Weinstein (2010) and Bilbiie et al. (2012) find product creation to be pro-cyclical, whereas product destruction and drop-out rates are counter-cyclical. This should rather affect old than new products. This means that at least some fraction of the sluggish demand levels inherent to downturns and recessions can not only be attributed to tighter budget constraints but also to the reduction of product variety. In total, combining the three transmission mechanisms of product innovations (direct demand effect, productivity effect and indirect demand effect) on employment growth, the net employment effect is ambiguous. Prior empirical evidence, however, has demonstrated that the labour-creating effect tends to outweigh the labour-destructing effect of product innovation leading to a positive net employment growth effect. Therefore, we expect the net effect of product innovation in general to be positive and to vary with the business cycle. If the net effect becomes negative, it is most likely to happen during a recession. Overall, we expect the net effect of product innovations to be pro-cyclical and smallest in recession periods.

Hypothesis H1c: The net employment effect of product innovations follows a pro-cyclical pattern, and is assumed to be smallest in recessions.

There are two basic mechanisms underlying the employment growth effect of process innovations: (i) a labour-destructing productivity effect and (ii) a labour-creating price effect. During downturns and recessions, the lack of demand may discourage the introduction of new products but increases the competition based on costs and prices (Spiegel and Stahl, 2014). In this situation, process innovations play an important role in improving productivity, which goes at the cost of job losses (Pianta and Lucchese, 2012). For a demand-inducing price-effect to occur, the cost reductions need to be passed on to the product price. However, firms may be less inclined to reduce prices, as profits usually decline during downturns and recessions. Therefore, we expect the labour-destructing productivity effect to prevail during downturns and recessions. In contrast, process innovators may be less eager to increase productivity during upturn and boom periods. Tether and Tajar (2008) find that the main strength of process innovations is the flexibility and adaptability of production to market needs. This orientation of process innovators may allow them to better exploit generic periods of high demand on a large scale. Therefore, we expect that process innovators may be more focused on meeting the market needs during booms than during recessions. This is less likely to be job-destructing. Even if process innovators increase productivity during boom periods, we expect the labour-creating price effect to occur, at least in part. Overall, we expect either stronger net job destruction or less net job creation during downturns and recessions as compared to upturns and booms. This leads to the following hypotheses:

Hypothesis H2a: The labour-destructing productivity effect of process innovations is strongest during downturns and recessions, followed by upturns and booms.

Hypothesis H2b: Process innovations induce either stronger net job destruction or less net job creation in downturns and recessions than in upturns and booms.

The literature presented in Section 4.2.2 suggests that the employment effect of organisational innovations is driven by the same two mechanisms observed for process innovations. That is, a direct productivity effect may reduce the innovators' labour demand and a potentially counteracting price effect may stimulate firms' employment growth. Lundvall and Kristensen (1997) show that firms' propensity to use organisational innovations as an efficiency-enhancing instrument is increasing in competitive pressure. As discussed for process innovations, the competitive pressure is probably highest during downturn and recession periods. This rather reduces labour demand. For these reasons, we expect that the business cycle effects of organisational innovations on employment growth largely correspond to the effects of process innovations.

Hypothesis H3a: The labour-destructing productivity effect of organisational innovations is strongest during downturns and recessions, followed by upturns and booms.

Hypothesis H3b: Organisational innovations induce either stronger job destruction or less net job creation in downturns and recessions than in upturns and booms.

4.3 Empirical model

In order to test our hypotheses, we adopt the approach developed by Harrison et al. (2008, 2014) that establishes a theoretical link between firm-level employment growth and different types of innovations. The main virtue of the model is that it relies on innovation output indicators. This means that it incorporates the demand situation of the respective firms, which is an important element of firms' labour demand. Its empirical implementation is targeted at using information provided by CIS data. In its original form, the model has been used to analyse employment effects of product and process innovation for European, Latin American and Chinese firms (see e.g. Benavente and Lauterbach, 2007; Hall et al., 2008; Mairesse et al., 2011; Crespi and Tacsir, 2013; Harrison et al., 2014). We follow Peters et al. (2013) and Damijan et al. (2014) and extend the model by including organisational innovations as well. Furthermore, we estimate the model for a large set of European firms observed during a reasonably long period that covers different business cycle periods. In the following, we briefly describe the model; for more details see Harrison et al. (2008, 2014).

The model is based on a two-product framework, i.e. a firm can produce two different (sets of) products, at two points in time $t = (1, 2)$. At the beginning, at $t = 1$, a firm produces a certain product or product portfolio, which by definition is labelled as old (or existing) products. Between $t = 1$ and $t = 2$, a firm may introduce one or more new or significantly improved products (product innovations). The new products can (partially or totally) replace the old ones in case they are substitutes. They enhance the demand of the old product in case of a complementary relationship. Hence, at the end of that intermediate period, $t = 2$, the firm produces either only old products, only new products or both types of products.

To produce the respective output, we assume an underlying production function that is linear homogeneous in the conventional inputs labour, capital and material. In addition, the final output depends on Hicks neutral productivity of the respective product j at time t, captured by θ_{jt}. With respect to old products, a firm can increase the production efficiency between $t = 1$ and $t = 2$ by implementing process and organisational innovations. In addition to a firm's own innovation-related productivity improvements, productivity gains may be caused by learning effects, spillovers, inputs of higher quality, training, selling or shutting down of unprofitable business units or mergers and acquisitions. As by definition new products are not produced at $t = 1$, firms cannot improve the productivity of new products. However, it is important whether or not the productivity of new products will be higher or lower compared to the one of old products. Based on these considerations, Harrison et al. (2008, 2014) derive the following labour demand equation (for ease of presentation, firm indices i and time indices t are suppressed:

$$l = \alpha + y_1 + \beta y_2 + u \tag{4.1}$$

Employment growth l originates from four main sources in the model: (i) efficiency gains in the production of old products, α, (ii) the growth rate of the real output of old products, y_1, (iii) the real output growth rate due to new products, y_2 and (iv) the relative productivity of new products, β.[37] The error term u captures unanticipated productivity shocks in the production of old products at $t = 2$.[38]

The output growth of old products, y_1, is likely to depend on the demand for new products, at least to some degree. That is, it captures indirect demand effects: Negative output growth will arise if new products are substitutes to old products (cannibalisation effect), whereas the growth rate will be stimulated in case of a complementary relationship. Furthermore, the effect of y_1 also captures (i) demand changes provoked by innovations introduced by competitors (business stealing effects), (ii) demand increases due to innovation-related price reductions (price effect), (iii) changes in consumer preferences, (iv) policy-induced demand changes and (v) business cycle effects. Data limitations restrict us in disentangling the

[37] Please note that as new products have not been produced at $t = 1$, y_2 cannot measure the real output growth of new products. Instead, y_2 measures the output of the new products (excluding unanticipated shocks) at $t = 2$ relative to the output of the old products at $t = 1$. Therefore, it captures the real output growth rate *due to* new products.

[38] The production functions of old and new products at $t = 2$ include unanticipated productivity shocks u and v, respectively. In deriving equation (4.1), Harrison et al. (2014) show that v cancels out. The production functions of both products also allow for unobserved firm fixed effects, η_i in every period. These firm fixed effects also vanish in the growth rate formulation.

underlying effects from each other. However, the data we use allow us at least to separate the business cycle effects from the other demand-side effects.

The term βy_2 captures the *gross employment growth induced by new products*, which consists of two channels. The first one refers to the *demand growth due to new products* (relative to the old products), y_2. The second one, β, involves the *productivity effect of new products*. This relative productivity is defined as $\beta = \theta_{11}/\theta_{22}$, i.e. as efficiency of old products in $t = 1$, θ_{11}, relative to the efficiency of new products in $t = 2$, θ_{22}. Ceteris paribus, new products will generate higher employment growth if their production is less efficient than the production technology of the old products, i.e. if $\theta_{22} < \theta_{11}$. In contrast, new products will induce relatively less labour demand if new products are produced more efficiently, that is for $\beta < 1$. According to our hypothesis H1a, we expect β to be independent of the business cycle.

In principle, an increase in the efficiency in the production of old products reduces firms' labour demand. Hence, we expect α to be negative. Harrison et al. (2014) suggest separating the non-innovation-related and innovation-related efficiency improvements. With respect to the latter, they only account for process innovation-induced improvements. We extend the model by separately investigating the employment impact of efficiency improvements of organisational innovations as well. Rewriting equation (4.1) yields:

(4.2) $$l = \alpha_0 + \alpha_1 pc + \alpha_2 orga + y_1 + \beta y_2 + u$$

In addition to equation (4.1), equation (4.2) disentangles the productivity effect of old products into three components: α_0, α_1 and α_2. The first effect, α_0, represents the average efficiency gains of old products not related to innovations. The components α_1 and α_2 measure the *productivity effect, i.e. gross effect, of process (pc) and organisational ($orga$) innovations*, respectively.

Unfortunately, we cannot estimate equation (4.2) as we cannot observe real output growth rates in our data. Instead, we replace the unobserved real growth rates by the observable nominal growth rates measured as sales growth. This yields the following equation:

(4.3) $$l - (g_1 - \tilde{\pi}_1) = \alpha_0 + \alpha_1 pc + \alpha_2 orga + \beta g_2 + \varepsilon$$

The nominal sales growth of the old products, g_1, and of the new products, g_2, are defined as $g_1 = y_1 + \pi_1$ and $g_2 = (1 + \pi_2)y_2$. The coefficient of the real output growth of old products, y_1, is equal to one and can be subtracted from l. The variables g_1 and g_2 can be calculated by using CIS data presented in Section 4.4.1. The sales growth rate of the old products, g_1, is defined as the total sales growth rate minus the sales growth rate due to new products. The term π_1 measures the unobserved price growth rate of old products at the firm level. Potential data sources usually do not provide price data on a firm level. Therefore, we proxy π_1 by the price growth rate of old products at a 2-digit industry level, $\tilde{\pi}_1$. The firm-level indicator π_2 is defined as the price difference between new products at $t = 2$ and old products at $t = 1$ in relation to the price of the old products at $t = 1$. The problem is that we cannot observe this price information, not even on an industry level. However, substituting a real by a nominal growth rate requires price growth information to adequately estimate the effect. As a result, our estimation of β suffers from an endogeneity bias caused by measurement errors and we use an instrumental variable (IV) approach to deal with this endogeneity problem.[39] A similar

[39] We explain our identification and estimation strategy below in Section 4.4.4.

problem would arise for the estimated coefficients of α_1 and α_2 if $\tilde{\pi}_1$ was a weak proxy variable for π_1.[40] In this case the price growth on an industry level would substantially diverge from the firm-level price growth. Therefore, the new error term incorporates these potential sources of endogeneity, so that $\varepsilon = -E(\pi_1 - \tilde{\pi}_1) - \beta\pi_2 y_2 + u$.

Even in the case $\tilde{\pi}_1$ is a good proxy variable for π_1, what we assume, the estimates of our innovation indicators can still suffer from an endogeneity bias. For instance, innovations are typically the result of investment decisions. If those decisions were correlated with any unobserved productivity shocks u appearing at $t = 2$ the estimated coefficients would indeed be biased. However, those decisions usually take place before the realisation of the shocks, i.e. before $t = 2$. This means that we do not expect serious endogeneity problems due to simultaneity. This has been confirmed by Harrison et al. (2014) who tested the exogeneity assumption of process innovations for manufacturing firms of four different European countries and did not find evidence for process innovations to be an endogenous explanatory variable in the econometric model.

Overall, subtracting the proxy for the real output growth of old products, $(g_1 - \tilde{\pi}_1)$, from employment growth, l, allows us to estimate the gross effect of process, organisational and product innovations.[41] Indeed, we cannot directly estimate the indirect demand effect, thus the net employment growth effect (H1c) of product innovations. In order to do so, we would need more detailed demand data to disentangle the different components of changes in y_1. However, as we will explain in more detail in Section 4.5.1.2 and Section 4.5.2.2, we will use a decomposition analysis to show the indirect and net employment growth effect for product innovators. Unfortunately, this is not possible for the net effect of process and organisational innovations. Therefore, the analysis of hypotheses H2b and H3b remain open for future research.

4.4 Data and estimation method

4.4.1 Data and variables

We use micro data from the European-wide Community Innovation Survey (CIS).[42] This survey rests on a European-wide harmonised questionnaire. It is biannually conducted by the national statistical offices or legalised national institutions of the European Union's member states, Iceland and Norway.[43] The CIS applies the definitions and methodology of the Oslo Manual on innovation surveys (see OECD and Eurostat, 2005). The target population covers all legally independent enterprises with 10 or more employees in manufacturing, mining, energy and water supply and selected services. The survey collects data on firms' innovation expenditures, different innovation output indicators and other business-related information, e.g. employment and sales. Each CIS wave covers a three-year period. Hence, we have calculated all our growth rates between t and t-2.

We employ five waves of CIS data that cover the years 1998-2000 (CIS3), 2002-2004 (CIS4), 2004-2006 (CIS2006), 2006-2008 (CIS2008) and 2008-2010 (CIS2010). For the empirical analysis, we focus on employment effects of innovation in manufacturing firms only. Furthermore, we define two samples. Sample 1 includes 201,691 firm-year observations and

[40] The estimates are only unbiased if $\tilde{\pi}_1$ corresponds to π_1. We would underestimate the productivity effects of process and organisational innovation, otherwise.

[41] Instead of using $l - (g_1 - \tilde{\pi}_1)$ as dependent variable, we could have used l as dependent variable and $(g_1 - \tilde{\pi}_1)$ as additional explanatory variable. However, in line with the model, we would have restricted the coefficient to be one, which would have generated the same results. Therefore, we still can interpret the results in terms of employment growth.

[42] We accessed CIS micro data at Eurostat's Safe Centre in Luxembourg.

[43] Prior to CIS2006 (2004-2006), the survey was conducted every fourth year.

depicts our main sample. It is used for estimating the econometric model with organisational innovation (equation (4.3)). One limitation of the data is that only a limited number of countries provided information on organisational innovation in CIS2006 as this question was not compulsory in this wave (see Table 4.A.1 in the Appendix). As the period 2004-2006 marked a boom period in many European countries, the drop in the number of observations is particularly strong for the boom sample. To check whether this substantially affects the estimated employment effects of product and process innovation, we additionally estimate the model excluding organisational innovation. This allows us to use sample 2 that contains 225,544 firm-year observations. Table 4.1 gives an overview of the distribution of the CIS waves. The distribution among the CIS waves shows that the first three CIS waves exhibit the smallest sample sizes, whereas more than half of the observations stem from CIS2008 and CIS2010 in sample 1.

Within the manufacturing sector, the manufacturing of basic and fabricated metals, food and beverages as well as the textile industry hold the highest shares of observations (see Table 4.A.2 in the Appendix). The vehicle industry along with the industries of chemicals, rubber and plastics as well as non-metallic mineral products, have the lowest shares in our sample.[44]

Table 4.1: Distribution of CIS sample by waves

CIS-waves	Observation period	Sample 1		Sample 2	
		N	%	N	%
CIS 3	1998-2000	40,044	19.85	40,044	17.75
CIS 4	2002-2004	43,397	21.52	43,431	19.26
CIS2006	2004-2006	13,116	6.50	35,970	15.95
CIS2008	2006-2008	52,008	25.79	52,870	23.44
CIS2010	2008-2010	53,126	26.34	53,229	23.60
Total	1998-2010	201,691	100	225,544	100

Source: CIS3, CIS4, CIS2006, CIS2008 and CIS2010, Eurostat; authors' own calculation.
Note: Sample 1 refers to the model that includes organisational innovation; sample 2 refers to the model that excludes organisational innovation.

Although all EU countries are required by law[45] to conduct the CIS, they are not obliged to transfer micro data to Eurostat. In total, micro data are available for all five waves for 11 out of 26 countries. Five countries provide micro data only for one or two waves. The sample sizes between the countries differ substantially (see Table 4.A.1 in the Appendix), partly due to the country size and partly because the CIS is compulsory for the firms in some countries like France and Italy, whereas it is voluntarily in other countries. To get representative results, we apply weighting factors to all descriptive statistics and estimations.[46]

Another limitation of the data is that firm-level observations cannot be linked between subsequent CIS waves due to missing firm identifiers. Hence, we can only apply pooled OLS and IV estimators. In order to account for the fact that some firms are repeatedly observed and the i.i.d. assumption may be violated, we will use clustered standard errors at the industry-country level to allow for correlation among the error terms within the cluster.

[44] In a companion paper, we investigate the effects of innovations on employment growth over the business cycle on a sectoral and industry level (see Dachs et al., forthcoming).

[45] Up to 2010, CIS has been collected under Commission Regulation (EC) No 1450/2004. From 2012 onwards, Commission Regulation No 995/2012 applies.

[46] Weighting is implemented by using sample weights that extrapolate to the population number of firms in each stratum.

4.4.2 Variables

In accordance with the underlying model, the dependent variable, EMP, is defined as $l - (g_1 - \tilde{\pi}_1)$. The employment growth, l, is measured as the relative change in the number of employees (head counts) between t and t-2. The real output growth due to old products, $g_1 - \tilde{\pi}_1$, denotes the difference between (i) the nominal sales growth rate of old products (g_1 / SGR_OLDPD) and (ii) the growth rate of prices for old products at the industry level ($\tilde{\pi}_1$ / PRICEGR).[47] The nominal sales growth rate due to old products (g_1 / SGR_OLDPD) is calculated as the total sales growth rate minus the sales growth rate due to new products (g_2 / SGR_NEWPD; see below). To calculate $\tilde{\pi}_1$ we use producer price indices at the 2-digit country-industry level as published by Eurostat.

Process innovation (pc) is represented by the dummy variable PC that takes on the value one if firms have introduced only process innovations but no product innovations between t and t-2. According to the Oslo Manual, a process innovation is the implementation of a new or significantly improved production process, distribution method, or supporting activity. This definition includes process innovations that are introduced to support the launch of product innovations (see OECD and Eurostat, 2005, paragraph 164). According to our theoretical model, however, α_1 captures efficiency gains of process innovation related to the production of old products. Our focus on pure process innovators in the empirical analysis allows us to identify the employment effect of process innovations related to old products more accurately.

Organisational innovations involve new methods in the firms' business practices, workplace organisations or external relations. According to the Oslo Manual, they are intended to e.g. lower administrative costs and to increase labour productivity. However, they are not considered as an enabler for product innovations. One example of an organisational innovation is firms' reduction of hierarchy levels (delayering). A flatter management structure lowers costs and should increase firms' productivity as there are fewer management hurdles to overcome within a decision process. We measure organisational innovations ($orga$) by the indicator ORGA that takes on the value one if firms introduced at least one organisational innovation between t and t-2.

Our key variable for measuring product innovation output is the sales growth rate due to new products (g_2). Its empirical counterpart, SGR_NEWPD, is calculated as year t's sales share with new products, which have been introduced between t and t-2, multiplied by the ratio of year t's sales divided by the sales of t-2.

Beyond the information required by the model's structural equation, employment growth is likely to be influenced by a set of other characteristics. An important determinant for employment growth is firm size. According to Gibrat's law, firms grow proportionally and independently of firm size. In contrast, Mansfield (1962) finds that smaller firms' growth rates are higher and also more volatile. Jovanovic (1982) provides a theoretical background for Mansfield's related analyses. His model suggests that surviving young and small firms grow faster than older and larger ones because of managerial efficiency and learning by doing. To control for size effects we include the dummy variables, MEDIUM – taking on the value one for firms with 50-249 employees – and LARGE, for firms with at least 250 employees.[48] Firms with less than 50 employees, SMALL, build our reference category. All size dummies are related to the period t-2. Furthermore, we control for ownership effects as employment grows slower and is also more volatile in foreign-owned firms (Dachs and Peters 2014). We include two dummy variables indicating that a firm belongs to a firm group that

[47] Lower-case letters denote the model variables whereas upper-case letters describe their empirical counterparts in the data. Remember that our growth rates are defined as the growth between t and t-2.

[48] To further scrutinize size heterogeneity, we split our sample into SMEs and large firms (see Section 4.5.2).

has a domestic (DGP) and foreign headquarter (FGP), respectively. Domestic unaffiliated firms serve as reference group (DUF).[49] A set of time, industry and country dummies based on the information presented in Table 4.A.1 and Table 4.A.2 is also included.

To properly examine business cycle effects, we split our estimation sample into the four phases of the business cycle. In general, the business cycle describes fluctuations in economic activity that an economy experiences over a period of time. A business cycle consists of four phases: upturn, boom, downturn and recession. Our analysis uses real GDP growth rates on a country level, provided by Eurostat. Based on that, we define our business cycle indicator as follows:

Table 4.2: Definition of the four business cycle phases

Business cycle phase	GDP growth is…
Upturn	increasing and positive
Boom	increasing and positive and subsequently decreasing
Downturn	decreasing but (still) positive
Recession	negative

One potential issue is the time period used to calculate this indicator. Statistical offices often use quarterly data on GDP growth to define a business cycle. In empirical work, it is also common to employ one-year growth rates. The CIS data covers a three-year period, in CIS2010 for instance the period 2008-2010. Hence, we use two-year GDP growth rates, i.e. in the example above the growth rate between 2008 and 2010.

Splitting the sample according to the business cycle phases ignores the information about the strength of GDP growth, which varies considerably across European countries. For this reason, we include in our estimations the information about country-level real GDP growth rates (GDPGR) between t and t-2. This captures general demand effects. Firm-specific demand effects are already covered by g_1 and g_2. Therefore, our equation to be estimated is the following:

$$EMP_{t|t-2} = \alpha_0 + \alpha_1 PC_{t|t-2} + \alpha_2 ORGA_{t|t-2} + \beta SGR\_NEWPD_{t|t-2} + X_t\gamma + \varepsilon_t \tag{4.4}$$

The matrix X_t includes our control variables MEDIUM, LARGE, DGP, FGP and GDPGR as well as the time, industry and country dummies for each firm i at time t. The remaining variables, the error term ε_t and γ in equation (4.4) denote vectors.

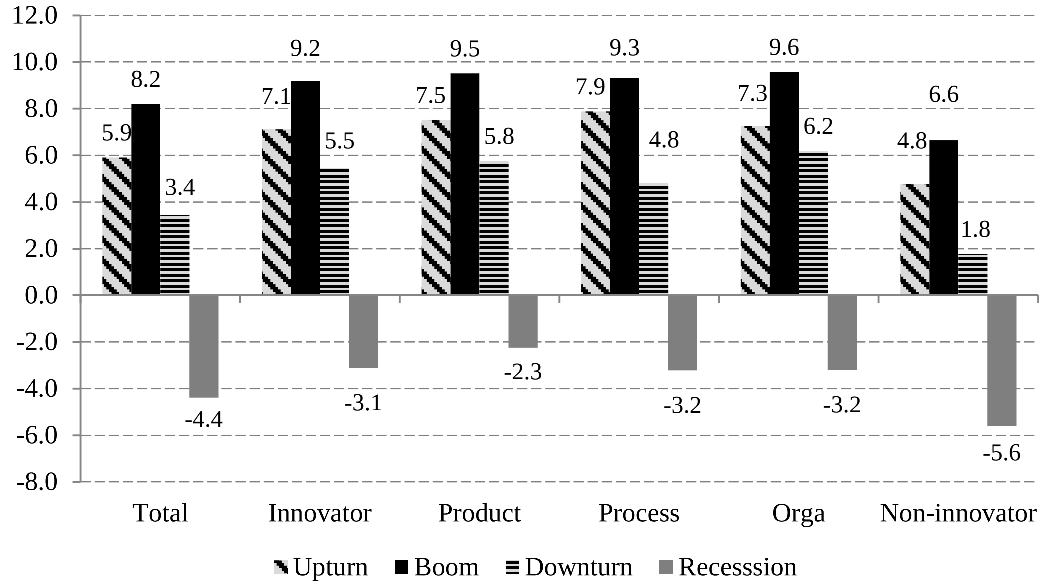
4.4.3 Descriptive statistics

About half of the firms (49.5%) can be classified as innovators having introduced at least one product (27%), process (11%) or organisational innovation (32%) (see Table 4.A.3 in the Appendix). This section presents basic descriptive results on the relationship between innovation and employment growth in different phases of the business cycle. For the total sample, Figure 4.1 shows that the average employment growth rates across all firms follow a pro-cyclical pattern. During upturn periods, firm-level employment has grown by 5.9%. It has increased by 8.2% during booms, whereas the growth rate diminished to 3.4% during downturn periods. The level of employment has been reduced by -4.4% during recessions.[50]

[49] See Table 4.A.3 for a distribution of the respective firm groups included in our sample.

[50] The employment growth rates are not directly comparable to official employment statistics. First, CIS applies the lower threshold of 10 employees. Second, employment changes due to firms exiting and entering are not captured by CIS data because survey response is conditional on surviving and employment growth rates are not defined for newly established

Figure 4.1: Employment growth by innovation status in different business cycle periods, in %



Source: CIS3, CIS4, CIS2006, CIS2008, CIS2010, Eurostat; authors' own calculation.

Note: Weighted figures; the group "Innovator" refers to firms that have implemented at least one process, product or organisational innovation between t and t-2.

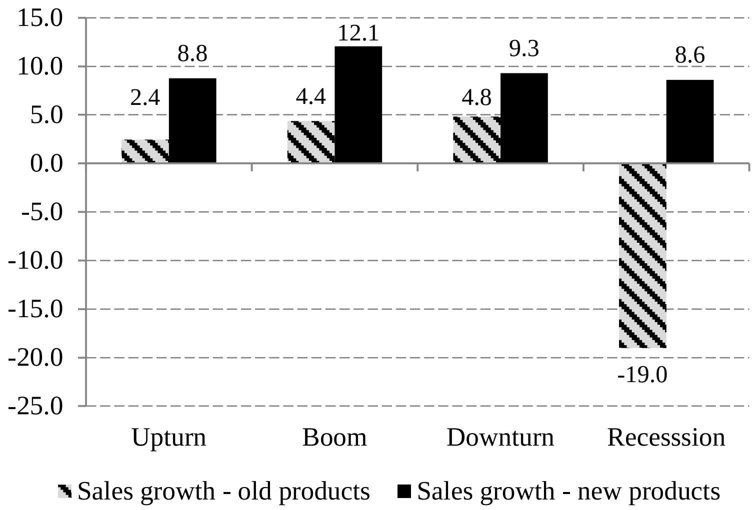
This pro-cyclical relationship holds for each type of innovator and non-innovator, respectively. It means that each group has suffered from employment reductions during recessions and has achieved employment growth during the other periods. More importantly, we observe substantial differences in average employment growth between the group of innovators and the group of non-innovators in each phase of the business cycle. For instance, during booms, innovators have raised their employment level by 9.2%, whereas non-innovators' employment has increased by 6.6%. Such a strong difference is observed for all types of innovators. The most notable difference concerns the recession period. Innovators have decreased their employment level by -3.1% during recessions, whereas non-innovators have cut employment by almost twice as much (-5.6%). This implies that innovators, particularly product innovators, have been more resilient to periods of negative economic growth. The difference in the employment growth rates between innovators and non-innovators may be due to the innovators' superior adaptability to shocks (Meghir et al., 1996). Accordingly, innovating firms are more flexible and have lower adjustment costs of employment when faced with negative shocks. Of course, it might also be that innovators and non-innovators differ in other firm characteristics that contribute to the better employment performance of innovators in general and to the stronger resilience of innovators in recessions in particular. The econometric analysis is aimed at disentangling the role of innovation while controlling for these other firm characteristics.

Figure 4.2 brings two key variables of the empirical model into focus: the average nominal sales growth rates due to new and to old products. New product sales as well as old product sales follow a pro-cyclical pattern. New product sales have increased by 8.8% during upturn periods and by 12.1% during booms. The strong demand has slowed down to 9.3% during downturn periods. The weakest demand has occurred in recessions, with a growth rate of 8.6%. Pairwise mean difference tests show that the average sales growth rates due to new products are significantly different at the 1% level between upturn and boom, boom and

firms. Third, official statistics are based on a different calculation method which is the ratio of the sum of changes in employment for all firms to the sum of employed personnel.

downturn and downturn and recession, respectively. Hence, we find support for our hypothesis H1b. New product sales are pro-cyclical and always positive. Despite significant differences across business cycle periods – except for the comparison between upturn and recession – it is remarkable how much sales growth is generated with new products even in recessions. If we focus only on product innovators, the sales growth due to new products is about 30% in the recession, only little less than in the boom period (33%), see Table A-5. This finding will become important in explaining employment growth differences of innovators and non-innovators in the recession.

Figure 4.2: Sales growth due to new and old products, in %



Source: CIS3, CIS4, CIS2006, CIS2008, CIS2010, Eurostat; authors' own calculation.
Note: Weighted figures.

Sales growth due to old products is substantially lower than due to new products in all phases of the business cycle. While the gap remains rather stable for upturn, boom and downturn – ranging from 4.5 to 7.7 percentage points – it stands out in the recession. Sales with old products have severely suffered from a drop in demand and declined by -19%. Table 4.A.5 in the Appendix shows that this substantial decline is partly due to a reduction in demand for old products of product innovators (-37%). It may have been caused by significant product cannibalisation or a reduction in the innovators' product range. Another explanation relates to tighter budget constraints during recessions. The potential for budget restrictions is indicated by the sales loss of non-innovators, i.e. firms that only offered old products and did not introduce any innovation between t and t-2. Their sales growth rate decreased by -12.5% during recessions. This decline is substantially larger than the *net* loss in sales of product innovators (-7.1%).

4.4.4 Estimation approach and identification

As discussed in Section 4.3, the estimation of the relative productivity effect of product innovation, β, is subject to a measurement error of the sales growth rate due to new products. Therefore, we employ a weighted instrumental variable (IV) approach to estimate equation (4.4) consistently. In our case, variables qualifying as instruments should be correlated with the sales growth due to new products (i.e. innovation success) and should be uncorrelated with the error term. In particular, the instruments have to be uncorrelated with the relative price difference of new and old products. We cannot use any lagged values of the endogenous right-hand variable as instrument because Eurostat does not provide firm identifiers. Instead, our identification strategy is based on three external instruments. We expect these variables to be important in explaining innovation success and to be uncorrelated with the relative price difference of new to old products.

Following Harrison et al. (2014), we use RANGE as instrument. RANGE is a binary indicator measuring whether the implemented product innovations have been aimed at increasing the product range or not. We assume RANGE to be correlated with the expectations of new product sales. Enlarging the range of products is a strategic decision that may require more resources than other product innovations. We expect that those firms put more effort into the development and the market introduction. This means, they may spend more on e.g. R&D, the product design and marketing activities. If firms invest more for product innovations it should also have a positive effect on the new products' success. Enlarging the range of products, however, does not imply any particular direction of the changes in prices. New products added to the firm's product portfolio might be of higher (lower) quality sold at higher (lower) prices than existing products of similar quality and price. Our second instrument is a binary indicator as well. It takes on the value one if the firm actively cooperated in innovation projects with other agents, COOP. Other agents include, for instance, suppliers, research institutions and competitors. Firms benefit from knowledge spillovers in cooperation projects. We expect these spillovers to increase the likelihood of successfully developed new products which should be in turn correlated with higher expected new product sales. Furthermore, cooperating firms may establish new ways (or channels) of distributing the products. This should also be correlated with higher expected sales with new products. However, we do not expect this to significantly affect the relative price between old and new products. Our third instrument, RD, indicates whether a firm performs R&D activities on a continuous base or not. A continuous research effort should be related to a higher likelihood of inventing new technologies and as a result of higher expected sales with new products. However, we do not expect a more continuous research effort to be substantially linked to the relative price difference.

4.5 Empirical evidence on employment effects of innovation over the business cycle

4.5.1 Full sample results

4.5.1.1 Regression results

Table 4.3 presents the regression results of the basic OLS estimations. We split the sample into the four phases of a business cycle, i.e. upturn, boom, downturn and recession. The coefficient of the sales growth rate due to new products (SGR_NEWPD) is central to our analysis on the relationship between employment growth and product innovation.

The coefficient measures the average employment effect of the relative efficiency of the production between old and new products. The results show that the relative production efficiency, $\hat{\beta}$, is smaller than one. This means, producing new products is more efficient than producing old products resulting in less labour demand. Efficiency gains range between 9.7% and 13.4%. To test whether these estimates are significantly different from one, we performed Wald tests. Each displayed p-value of the Wald test suggests that the relative production efficiency is significantly smaller than one. However, we suspect SGR_NEWPD to be endogenous due to measurement error and hence $\hat{\beta}$ to be downward biased. To address endogeneity, we conduct IV estimations as explained in Section 4.4.4.

Table 4.3: Employment effects of innovation over the business cycle, OLS estimations

	Business cycle phase			
Dep. var.: EMP	**Upturn**	**Boom**	**Downturn**	**Recession**
SGR_NEWPD	**0.866*****	**0.892*****	**0.879*****	**0.903*****
	(0.014)	(0.015)	(0.011)	(0.013)
PC	**-3.090*****	-1.374	**-3.486*****	-1.188
	(0.817)	(1.310)	(0.846)	(0.887)
ORGA	**-0.967****	**1.360***	0.376	0.187
	(0.398)	(0.693)	(0.548)	(0.457)
GDPGR	**3.727*****	**-0.509****	**-0.611*****	**-0.362***
	(0.554)	(0.202)	(0.177)	(0.217)
MEDIUM	**-2.906*****	0.084	-0.845	**-1.910*****
	(0.470)	(0.859)	(0.556)	(0.499)
LARGE	**-4.263*****	**-3.135****	-0.777	**-3.792*****
	(0.613)	(1.216)	(0.725)	(0.648)
DGP	-0.957	**3.330*****	0.629	**1.327***
	(0.708)	(1.164)	(0.655)	(0.676)
FGP	-0.787	0.969	0.237	**-1.730*****
	(0.791)	(1.159)	(0.657)	(0.650)
Constant	**-67.655*****	1.383	**-14.920*****	**2.972***
	(7.270)	(1.729)	(2.614)	(1.600)
Observations	67,468	15,863	67,179	51,181
R2_adjusted	0.383	0.495	0.393	0.467
Further test:				
Wald-test for β=1 (p):	**0.000*****	**0.000*****	**0.000*****	**0.000*****

Source: CIS3, CIS4, CIS2006, CIS2008 and CIS2010, Eurostat; authors' own calculation.

Note: * p<0.1; ** p<0.05; *** p<0.01; weighted OLS estimations; clustered standard errors in parentheses (clustered by 2-digit industry and country); time, industry and country dummies are included and each set of dummies is jointly significant.

Our main results, the IV estimates, are presented in Table 4.4. The test on exogeneity corroborates our suspicion that the sales growth due to new products is endogenous. The tests reject the null hypothesis of exogeneity for all business cycle phases at least at the 5% level. The IV results disclose positive and significant estimates for $\hat{\beta}$ across all phases of the business cycle. These estimates are larger than the OLS estimates. Except for the downturn period, the coefficients are only slightly smaller than one. The Wald tests confirm that each of the four coefficients is not significantly different from one. Hence, new and old products are produced equally efficient, on average. According to the structural model, the coefficient indicates that a 1% increase in the sales due to new products leads to a 1% increase in gross employment, independent of the cyclical situation. The finding that $\hat{\beta}$ is not significantly different from one in all four estimates confirms our hypothesis H1a stating that the productivity effect of product innovation is independent of the business cycle.

The coefficient of PC measures the productivity effect (gross employment effect) of process innovations. The significantly negative coefficients in the upturn and downturn period indicate that the implemented process innovations have been labour-destructing, on average. The coefficients are negative, though insignificant for booms and recessions. The finding for the boom period is in line with our hypothesis H2a. We expect either no or at least the smallest labour-destructing productivity effect during booms because process innovations are more likely to be aimed at increasing capacity and flexibility than efficiency in this situation. The insignificant estimate for the recession, however, is counterintuitive as we expected stronger negative effects for downturns and recessions. For this reason, we can only partially confirm hypothesis H2a. The employment effects of organisational innovations are very similar to the ones of process innovations. That is, as expected organisational innovations significantly reduce the innovators' labour demand during upturn and downturn periods. The positive though insignificant effect in the boom period is again in line with hypothesis H3a.

Like for process innovation, we do not find significant labour-displacing effects of organisational innovations in the recession. This similarity may be attributable to the assumption that organisational and process innovations rely on the same channels to influence employment growth. As a result, we only partially confirm hypothesis H3a as well.

Table 4.4: Employment effects of innovation over the business cycle, IV estimations

	Business cycle phase			
Dep. var.: EMP	**Upturn**	**Boom**	**Downturn**	**Recession**
SGR_NEWPD	**0.991*****	**0.971*****	**1.003*****	**0.988*****
	(0.022)	(0.031)	(0.026)	(0.029)
PC	**-1.665****	-0.173	**-1.816***	-0.214
	(0.821)	(1.401)	(0.941)	(1.038)
ORGA	**-2.284*****	0.536	**-1.393****	-0.716
	(0.463)	(0.743)	(0.614)	(0.501)
GDPGR	**3.637*****	2.823	**-0.600*****	-0.017
	(0.555)	(1.812)	(0.175)	(0.278)
MEDIUM	**-3.090*****	-0.014	**-1.260****	**-2.026*****
	(0.463)	(0.863)	(0.597)	(0.503)
LARGE	**-4.728*****	**-3.577*****	**-1.358***	**-3.976*****
	(0.612)	(1.284)	(0.791)	(0.667)
DGP	**-1.487***	**3.203*****	0.566	**1.244***
	(0.792)	(1.165)	(0.648)	(0.663)
FGP	-1.113	1.039	0.123	**-1.825*****
	(0.804)	(1.147)	(0.659)	(0.628)
Constant	**-67.158*****	**-33.436****	**-15.094*****	**3.013***
	(7.291)	(15.817)	(2.647)	(1.647)
Observations	67,468	15,863	67,179	51,181
R2_adjusted	0.377	0.492	0.387	0.464
Further tests:				
Wald-test for β=1 (p):	0.691	0.349	0.908	0.681
Test on exogeneity (p):				
SGR_NEWPD	**0.000*****	**0.004*****	**0.000*****	**0.024****
Test on instrument validity				
Hansen J test (p):	0.375	0.311	0.160	0.220
Difference-in-Hansen test (p)				
RANGE	0.237	0.132	0.264	0.163
COOP	0.469	0.340	**0.056***	0.929
RD	0.162	0.413	0.809	0.112
First stage results (SGR_NEWPD)				
RANGE	**21.885*****	**20.747*****	**23.241*****	**19.504*****
	(0.771)	(1.226)	(0.956)	(1.027)
COOP	**4.984*****	**4.852*****	**5.602*****	**2.717****
	(0.801)	(1.808)	(0.770)	(1.104)
RD	**10.112*****	**7.172*****	**5.731*****	**5.937*****
	(1.279)	(1.298)	(1.392)	(1.439)
F test on excluded instruments (F):	**436.24*****	**228.91*****	**321.22*****	**265.71*****
Test on underidentification				
Kleibergen-Paap LM test (chi2):	**297.66*****	**61.60*****	**1326.52*****	**706.99*****
Test on weak instruments				
Kleibergen-Paap F test (F):	**560.83*****	**300.28*****	**801.49*****	**346.56*****
Inference robust to weak identific.				
Anderson-Rubin Wald test (chi2):	**926.19*****	**462.64*****	**986.76*****	**335.10*****
Stock-Wright LM test (chi2):	**65.38*****	**45.52*****	**87.83*****	**48.95*****

Source: CIS3, CIS4, CIS2006, CIS2008 and CIS2010, Eurostat; authors' own calculation.

Note: * p<0.1; ** p<0.05; *** p<0.01; sample 1; weighted IV regressions; clustered standard errors in parentheses; time, industry and country dummies are included and each set of dummies is jointly significant.

With respect to the control variables, an interesting finding is that affiliates of foreign multinational firms (FGP) grow with a significantly lower rate reduced during recessions than domestically owned firms. An explanation could be that foreign-owned firms are more exposed to fluctuations of the world market via exporting activities. In addition, the negative coefficient may also imply that multinational firms rather prefer to lay off employees abroad than at home during recessions. The results furthermore corroborate that firm size matters for employment growth. In all business cycle phases, large firms (LARGE) and medium-sized firms (MEDIUM) have lower employment growth rates than the reference category of small firms, even though the effect of MEDIUM for booms is not significant. This is in line with findings of Mansfield (1962) and the predictions of Jovanovic (1982). Furthermore, higher GDP growth is associated with significantly higher employment growth rates during upturn periods. The negative effect of GDP growth for downturn periods is, however, a bit puzzling. One explanation could be that a relatively high GDP growth rate within a downturn period may mean that the downturn "has just" started.[51] In this situation, firms may anticipate a downturn period. As a result, they may become more reluctant in hiring new employees at the onset of an economic downturn, which would reduce the firms' employment growth. This partly prevents the situation of dismissing employees due to excessively high labour costs if product demand further decreases. The national labour markets of EU countries are relatively well protected against dismissals. For instance, many of the EU countries, which are also members of the OECD, have strict employment protection laws (see OECD, 2013b, Chapter 2). Hence, it is not easily feasible for firms to lay off employees. The insignificant effect for recession periods implies that once GDP growth becomes negative the exact level of the economic slump does not significantly affect the firms' labour demand.

We carefully test our identification strategy using various tests. The consistency of the IV estimator depends on the validity of instruments. Therefore, we perform a Hansen J test on overidentifying restrictions for overall instrument validity. As we use three instruments, we also perform the Difference-in-Hansen C test to test for exogeneity of a single instrument. Using a conventional level of significance of 5%, all tests confirm that our instrument set is valid (see Table 4.4, Table 4.5 and in Section 4.5.2.1 Table 4.6 as well).[52] In addition, we check for non-weakness of the instruments. Weak instruments can lead to a large relative finite-sample bias of IV compared to the bias of OLS. All first stage regressions show our instruments to be strongly correlated with SGR_NEWPD, as is also supported by the significant test statistics of the Anderson-Rubin Wald test and the Stock-Wright LM test. Furthermore, the F test of excluded instruments always yields a statistic clearly being larger than ten. The regression output tables also display the Kleibergen-Paap LM test on underidentification as well as the F test proposed by Kleibergen and Paap (2006). All these tests indicate our instruments to be neither invalid nor weak.

As explained in Section 4.4.1, the information on organisational innovation is only available for very few countries in CIS2006. Including this indicator in our estimations reduces our sample by about 24,000 observations. This affects primarily the boom period. For this reason, we exclude organisational innovation and re-estimate our model using the larger sample 2 to check for substantial differences in the estimates. Table 4.5 presents the results of these regressions. Overall, the estimates are very robust. The main difference compared to Table 4.4 is that the estimated employment growth effect of SGR_NEWPD slightly weakens. However, based on the corresponding Wald test we still find all of them not to be significantly different from one on the conventional 5% level. Hence, the overall conclusion of hypothesis H1a

[51] Remember that according to our definition of a downturn, GDP growth is decreasing but not negative (see Table 4.2).

[52] At the 10% level, overall instrument validity cannot be rejected either. However, COOP and RANGE are only valid on a 5% level for downturns in Table 4.4, Table 4.5 and Table 4.6 and in booms in Table 4.5, respectively.

remains, i.e. the productivity effect of product innovations is independent of the business cycle.

Table 4.5: Employment effects of innovation over the business cycle (excluding organisational innovation), IV estimations

	Business cycle phase			
Dep. var.: EMP	**Upturn**	**Boom**	**Downturn**	**Recession**
SGR_NEWPD	**0.966***	**0.960***	**0.980***	**0.980***
	(0.020)	(0.023)	(0.022)	(0.027)
PC	**-2.283***	-0.698	**-2.080**	-0.359
	(0.799)	(0.935)	(0.841)	(0.988)
GDPGR	**3.703***	**-1.179***	-0.072	-0.006
	(0.551)	(0.456)	(0.219)	(0.277)
MEDIUM	**-3.113***	-0.004	**-1.386**	**-2.095***
	(0.450)	(0.714)	(0.544)	(0.515)
LARGE	**-4.906***	**-2.818**	**-1.755**	**-4.162***
	(0.587)	(1.106)	(0.762)	(0.685)
DGP	**-1.908**	**2.714***	0.427	**1.185***
	(0.786)	(0.986)	(0.616)	(0.668)
FGP	**-1.430***	1.208	-0.385	**-1.881***
	(0.779)	(0.980)	(0.621)	(0.615)
Constant	**-64.522***	3.931	**-21.702***	**2.973***
	(7.871)	(4.476)	(3.215)	(1.639)
Observations	70,396	31,345	72,519	51,284
R2_adjusted	0.381	0.463	0.377	0.463
Further tests:				
Wald-test for β=1 (p):	**0.079***	**0.077***	0.357	0.455
Test on exogeneity (p):				
SGR_NEWPD	**0.000***	**0.001***	**0.000***	**0.024**
Test on instrument validity				
Hansen J test (p):	0.319	0.245	0.153	0.223
Difference-in-Hansen test (p)				
RANGE	0.258	**0.095***	0.303	0.196
COOP	0.323	0.366	**0.054***	0.959
RD	0.139	0.327	0.703	0.102
First stage results (SGR_NEWPD)				
RANGE	**22.796***	**21.910***	**24.991***	**20.380***
	(0.779)	(1.043)	(0.943)	(1.024)
COOP	**5.818***	**5.724***	**6.180***	**3.470***
	(0.812)	(1.460)	(0.697)	(1.107)
RD	**11.241***	**8.168***	**6.320***	**6.495***
	(1.243)	(1.156)	(1.341)	(1.463)
F test on excluded instruments (F):	**452.6***	**320.64***	**342.75***	**245.55***
Test on underidentification				
Kleibergen-Paap LM test (chi2):	**347.76***	**145.61***	**1707.38***	**843.87***
Test on weak instruments				
Kleibergen-Paap F test (F):	**648.34***	**527.05***	**976.18***	**423.31***
Inference robust to weak identific.				
Anderson-Rubin Wald test (chi2):	**1054.43***	**667.65***	**1111.73***	**352.73***
Stock-Wright LM test (chi2):	**76.32***	**49.25***	**103.46***	**48.45***

Source: CIS3, CIS4, CIS2006, CIS2008 and CIS2010, Eurostat; authors' own calculation.

Note: * p<0.1; ** p<0.05; *** p<0.01; sample 2; weighted IV regressions; clustered standard errors in parentheses; time, industry and country dummies are included and each set of dummies is jointly significant.

4.5.1.2 Employment decomposition

The main specification we estimate by the IV approach allows us to identify the gross employment effect of product, process and organisational innovation. We complement our estimation results with a decomposition analysis. This allows us to quantify the absolute *contribution* of different sources to average employment growth for different types of firms. In particular, we are able to disentangle the employment effects of product, process and organisational innovations from effects originating from general demand and productivity trends. We follow the decomposition procedure proposed by Harrison et al. (2014) and Peters et al. (2013):

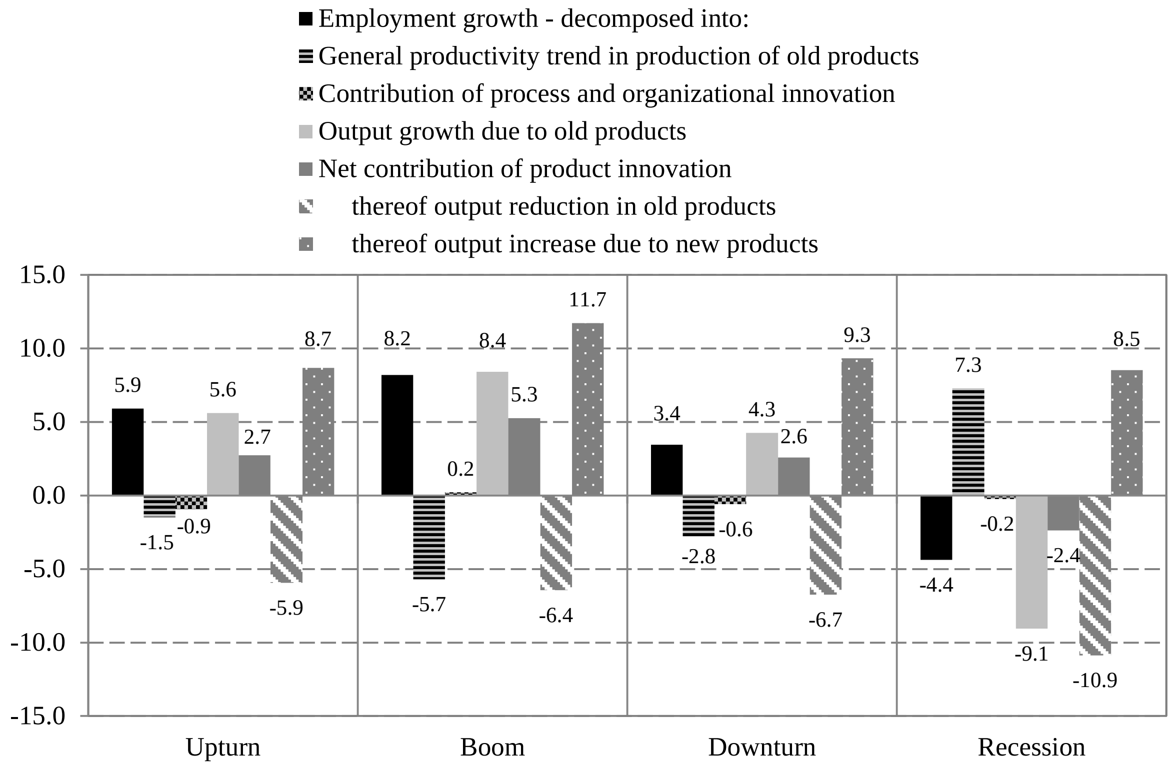
$$(4.5)\quad \bar{l} = \hat{\alpha}_0 + \hat{\alpha}_1\overline{pc} + \hat{\alpha}_2\overline{orga} + \overline{[1 - I(g_2 > 0)]}\ \overline{(g_1 - \tilde{\pi}_1)} + \overline{I(g_2 > 0)}\ \overline{(g_1 - \tilde{\pi}_1)} + \overline{I(g_2 > 0)}\hat{\beta}\bar{g}_2$$

In equation (4.5), bars denote mean values. Hence, the first term, $\hat{\alpha}_0$, measures the contribution of the general productivity trend in the production of old products to average employment growth, $\bar{l}$. It accounts for all changes in efficiency and employment that are not attributable to firms' own innovations. For instance, $\hat{\alpha}_0$ captures average employment effects of training, improvements in the human capital endowment and productivity effects from spillovers. The general productivity trend captures the general industry-, country-, time-, size-, GDP- and ownership-specific productivity trend. It is measured as the average effect across innovators and non-innovators. The second ($\hat{\alpha}_1$) and the third ($\hat{\alpha}_2$) terms capture the productivity effects of the share of process and organisational innovators, respectively.

The term $\overline{I(g_2)}$ measures the proportion of product innovators, whereas $\overline{1 - I(g_2)}$ measures the share of non-product innovators. This implies that the fourth component, $\overline{[1 - I(g_2)](g_1 - \tilde{\pi}_1)}$, captures the average employment growth caused by the average real growth of old product demand of the share of non-product innovators. A demand increase of old products can be due to a change in consumers' preferences, price reductions but also due to rivals' product innovations (business stealing effect). In contrast, the fifth term $\overline{I(g_2 > 0)}\ \overline{(g_1 - \tilde{\pi}_1)}$ accounts for indirect effects related to the demand for old products of the proportion of product innovators. These indirect demand effects may reflect cannibalisation effects, $\overline{(g_1 - \tilde{\pi}_1)} < 0$, and complementary effects, $\overline{(g_1 - \tilde{\pi}_1)} > 0$, respectively. $\overline{I(g_2 > 0)}\hat{\beta}\bar{g}_2$ measures the average employment growth due to average increases in the demand for new products of the share of product innovators. The sum of the fifth and sixth term denotes the net contribution of product innovators to employment growth.

To sum up, we calculate this decomposition by inserting the estimated coefficients $\hat{\alpha}_0$, $\hat{\alpha}_1$, $\hat{\alpha}_2$ and $\hat{\beta}$, the weighted shares of process, organisational, non-product and product innovators and weighted averages for employment, price and sales growth rates (either for all firms or for the corresponding group of firms). The decomposition analysis shows that the net contribution of product innovations to average employment growth depends on (i) the demand increase for new products, $\bar{g}_2$ ("innovation success"), (ii) the estimate of the relative production efficiency between old and new products, $\hat{\beta}$, (iii) possible shifts in the demand for old products, $\overline{(g_1 - \tilde{\pi}_1)}$, and (iv) the proportion of product innovators $\overline{I(g_2 > 0)}$.

Figure 4.3: Contribution of innovation types to employment growth in all phases of the business cycle, in %



Source: CIS3, CIS4, CIS2006, CIS2008, CIS2010, Eurostat; authors' own calculation.

Note: Decomposition of the weighted-average two-year employment growth rate; the decomposition is based on the regression results presented in Table 5.2.

Figure 4.3 provides a graphical illustration of the decomposition of average employment growth during the four phases of a business cycle. The sources (i) general productivity trend in the production of old products, (ii) productivity effect of process innovations and organisational innovations, (iii) output growth of non-product innovators due to old products and (v) the net employment contribution of product innovations sum up to the total average employment growth, which is also presented in Figure 4.1.[53] The figure further splits the net contribution of product innovation into the increase in output due to new products and shifts in demand for old products.

This figure reiterates the strictly pro-cyclical pattern of the average employment growth, as was shown in Figure 4.1. Most importantly, it discloses that the *net contribution of product innovation (dark grey bar) on employment growth is strictly pro-cyclical* as well. This implies that the net employment effect of product innovation is tightly connected to the specific macroeconomic growth period. According to this figure, product innovation has increased average employment by 2.7% during upturns. This shows that product innovation creates much more employment due to the demand effect than it destroys due to the productivity effect and substitution effect between old and new products. This effect is even stronger in an economic boom (+5.3%). In downturns, the gross employment creation effects of product innovation (white-dotted grey bar) shrink, but the net effect remains positive and of similar size than in upturns (2.6%). Only in the recession, the net contribution of product innovation is negative because output from new products does not grow fast enough to compensate losses in old products (-2.4%). These findings are in line with our hypothesis H1c. This pro-

[53] We combine the effects of process and organisational innovations because their separate contributions are very small in size.

cyclicality can be explained by the proc-cyclical direct demand effect of product innovation. But severe product cannibalisation and product range reduction also play an important role for this finding. In every business cycle phase, the introduction of new products is associated with a decline in the demand for old products (white-striped grey bar). This fall is rather low in periods of positive economic growth (-5.9% and -6.4%) but becomes much larger in recessions (-10.9%). Overall, our findings reveal that new products are an important driver for job creation in upturns, booms and downturns.

However, Figure 4.3 also reveals that – except for the recession – the main source for job creation is output growth due to old products of non-product innovators (light grey bar). Its contribution to average employment growth amounts to 5.6 percentage points during upturns, 8.4 during booms and 4.3 during downturns. At first glance, this finding might be counter-intuitive as the total sales growth rates of product innovators are larger across all periods than those of non-product innovators (Table 4.A.5) and given that we have found the same efficiency between old and new products. The larger employment contributions of old products are due to a much larger share of non-product innovators (73%) than product innovators (27%; see Table 4.A.3).

The second novel and intriguing finding of our analysis is that *product innovators are more resilient to recessions than non-product innovators*. Product innovators are able to compensate employment losses caused by demand reductions of old products by demand gains of new products. This ability is particularly valuable during recession periods. While product innovators have experienced a similar decline in employment due to the lower demand for old products (-10.9%) than non-product innovators (-9.1%), their employment gains from additional demand for their new products (+8.5%). This demand growth due to new products has remained remarkably high during the recession (see also Figure 4.2). As a result net employment losses of product innovators are significantly lower (-2.4%) in recessions than those of non-product innovators (-9.1%). Therefore, product innovations seem to have an employment-preserving effect and make the innovators more resilient when facing negative economic shocks. Labour-destructing productivity effects of process and organisational innovations do not affect employment growth on a large scale. Taken together, both types of innovations are weakly labour-creating during booms and they modestly displace labour demand during the three other business cycle phases, primarily during upturns and downturns.

Another factor dampening employment fluctuations over the business cycle is the general productivity trend in the production of old products. The general productivity trend curbed employment growth during upturns, booms and downturns, but it is strikingly positive during recessions (7.3%). Hence, results indicate firms' tendency towards labour hoarding during recession periods. This means, they reduce their staff by less than the demand for their products has fallen (Bhaumik, 2011). In general, labour hoarding results in a decrease of productivity. Our finding is in line with other studies. Leitner and Stehrer (2012) observe frequent labour hoarding during the recent crisis in Central and Eastern European countries. Labour hoarding may have occurred or intensified by effective short-time work programs during the 2008/2009 recession many EU governments have offered. Balleer et al. (2016) for Germany and Boeri and Brücker (2011) for a set of European countries find that short-time work had a positive effect in terms of job savings during the recent recession, even though it did not save as many jobs as the utilisation of short-time work could have saved (Boeri and Brücker, 2011).

4.5.2 Results for SMEs and large firms

4.5.2.1 Regression results

Small and medium-sized enterprises have been found to be the most important driver for employment growth (see Neumark et al., 2011; Haltiwanger et al., 2013). In particular, small enterprises are more flexible to react to new opportunities and are able to survive in niche markets. They primarily benefit from the personal engagement of the entrepreneur who transfers her knowledge on technologies and markets (see e.g. Thurik, 2009 for an overview). At the same time, there are many arguments put forward in the literature why large firms exhibit advantages in the innovation process (see e.g. Kleinknecht, 1989; Cohen, 1995, 2010). They have more internal financial means and better access to external funding to finance innovation projects more easily. Large and diversified firms also have more potential application possibilities for new knowledge (Rosenberg, 1990). Data from the recent economic crisis provides evidence that innovation activities in larger firms have been less affected by the recession. This supports the view that large firms have advantages in the innovation process (see e.g. Paunov, 2012; Rammer, 2012). This speaks in favour of a larger contribution of innovation to employment growth in large firms, in particular in the recession. To directly account for size differences in the employment effects of innovations, we split our sample into two size classes, i.e. SMEs (10-249 employees) and large firms (250+ employees). Table 4.6 presents the split sample estimation results of employment growth on innovation.

For both SMEs and large enterprises, higher sales growth rates due to new products are associated with significantly higher employment growth rates in all phases of a business cycle. The effect slightly differs between the phases but none of the coefficients is significantly different from one. This supports our hypothesis H1a for SMEs as well as for large firms. In the previous section we found that process innovations displace labour in upturns and downturns. Results in Table 4.6 show that the finding for downturns is primarily driven by SMEs, whereas process innovation-induced labour displacement effects in upturns are driven by large enterprises. This implies that there are different dynamics between SMEs and large firms regarding the labour destruction of process innovations. There are no significant labour-destructing effects in all other phases. Overall, we do not find support for H2a.

For SMEs, the findings for organisational innovations are in line with the results for the main sample (sample 1). This supports our hypothesis H3a. The exception is again the recession period for which we find a negative though insignificant effect. For large firms, we only confirm significant labour-destructing effects of organisational innovation during upturn phases.

Table 4.6: Employment effects of innovation over the business cycle, SMEs and large firms

	Number of employees: 10-249				Number of employees: 250+			
Dep. var.: EMP	**Upturn**	**Boom**	**Downturn**	**Recession**	**Upturn**	**Boom**	**Downturn**	**Recession**
SGR_NEWPD	**0.994*** **	**0.972*** **	**1.005*** **	**0.982*** **	**0.953*** **	**1.013*** **	**1.030*** **	**0.979*** **
	(0.024)	(0.032)	(0.025)	(0.029)	(0.031)	(0.049)	(0.042)	(0.045)
PC	-1.222	-0.350	**-1.795***	-0.413	**-2.999*** **	-0.175	0.521	0.443
	(0.792)	(1.493)	(0.977)	(1.076)	(1.107)	(2.064)	(1.193)	(1.214)
ORGA	**-2.065*** **	0.566	**-1.553** **	-0.813	**-2.871*** **	-1.695	-0.798	-0.839
	(0.449)	(0.703)	(0.648)	(0.515)	(0.695)	(1.053)	(0.749)	(0.565)
GDPGR	**3.772*** **	2.473	**-0.655*** **	0.169	**6.020*** **	1.129	**-0.949*** **	0.335
	(0.532)	(1.916)	(0.188)	(0.289)	(0.556)	(2.721)	(0.206)	(0.419)
DGP	**-1.564***	**3.159** **	0.654	0.763	**-3.393*** **	**2.090***	**-1.731***	-0.986
	(0.834)	(1.253)	(0.675)	(0.678)	(0.963)	(1.164)	(0.934)	(0.788)
FGP	-1.533	1.064	-0.108	**-2.384*** **	**-3.209*** **	-0.290	-0.419	**-3.426*** **
	(0.969)	(1.191)	(0.779)	(0.648)	(0.995)	(1.424)	(1.117)	(0.857)
Constant	**-68.663*** **	**-30.858***	**-15.021*** **	**3.088***	**-82.340*** **	-24.198	**-23.176*** **	0.359
	(7.064)	(16.670)	(2.794)	(1.767)	(6.263)	(24.882)	(3.080)	(2.271)
Observations	55,397	12,092	56,859	44,340	10,093	3,438	8,582	6,220
R2_adjusted	0.386	0.474	0.387	0.466	0.620	0.640	0.553	0.557
Further tests:								
Wald-test for β=1 (p):	0.806	0.387	0.834	0.532	0.123	0.798	0.479	0.634
Test on exogeneity: SGR_NEWPD (p):	**0.000*** **	**0.002*** **	**0.000*** **	**0.036** **	**0.000*** **	**0.003*** **	**0.002*** **	**0.046** **
Test on instrument validity								
Hansen J test (p):	0.654	0.465	0.180	0.391	0.189	0.983	0.490	0.373
Difference-in-Hansen test (p)								
RANGE	0.419	0.216	0.215	0.284	0.189	0.859	0.831	0.494
COOP	0.613	0.509	**0.065***	0.992	-	0.903	0.491	0.160
RD	0.357	0.460	0.999	0.195	0.189	0.961	0.258	0.587
F test on excluded instruments (F):	**447.52*** **	**207.5*** **	**312.97*** **	**283.25*** **	**298.38*** **	**48.29*** **	**125.47*** **	**79.06*** **
Test on underidentification: Kleib.-Paap LM test (chi2):	**265.775*** **	**61.121*** **	**1223.529*** **	**673.479*** **	**280.652*** **	**43.189*** **	**438.128*** **	**342.047*** **
Test on weak instruments: Kleib.-Paap F test (F):	**530.720*** **	**252.667*** **	**724.798*** **	**326.223*** **	**460.893*** **	**53.828*** **	**282.665*** **	**122.303*** **
Inference robust to weak identific.: And.-Rub. Wald test (chi2):	**858.517*** **	**428.026*** **	**991.793*** **	**324.717*** **	**449.902*** **	**215.935*** **	**258.671*** **	**142.058*** **

Source: CIS3, CIS4, CIS2006, CIS2008, CIS2010, Eurostat; authors' own calculation.

Note: * p<0.1; ** p<0.05; *** p<0.01; weighted IV regressions; clustered standard errors in parentheses. For large firms, estimates for the upturn period are based on the instrument set RANGE and RD because COOP turned out to be invalid in this regression. For convenience, we excluded the estimates of the first stage from this table. Each instrument, however, is positive and highly significant in the first stage as also indicated by the high F statistics.

4.5.2.2 Employment decomposition

Table 4.7 presents the decomposition results for the different size classes. Average employment growth exhibits a pro-cyclical pattern for both SMEs and large enterprises. In this respect, it is particularly intriguing that large firms on average have only created employment during boom phases. In contrast, average employment growth is positive for SMEs in all phases of the business cycle except for the recession. The decomposition for SMEs is very similar to the one for the total sample presented in Figure 4.3, which is not surprising given their weight in firm population. That is, product innovation is an important driver of employment growth in SMEs. The net employment effect of product innovation is pro-cyclical and positive in upturn, boom and downturn periods. However, in all three business cycle phases, the largest contribution to average employment growth in SMEs stems from output growth for existing products of non-product innovators. This pattern reverses in the recession. Whereas SMEs without product innovations experience a strong decline in their demand for existing products, SMEs introducing new products yield new product sales that have almost been sufficiently high to compensate for the loss in demand of old products. This creates stronger resilience of product-innovating SMEs in recession periods. Labour-destructing effects of process and organisational innovations are small in SMEs, in particular compared to those generated by the general productivity trend. The recession period is again an exception in which the general productivity trend indicates substantial labour hoarding in SMEs.

Table 4.7: Contribution of innovation to employment growth for SMEs and large firms, in %

Size	Components	Upturn	Boom	Downturn	Recession
10-249 employees	**Employment growth** - decomposed into:	**4.8**	**7.4**	**2.8**	**-4.8**
	General productivity trend in production of old products	**-2.5**	**-5.6**	**-2.9**	**7.3**
	Contribution of process and organisational innovation	**-0.8**	**0.2**	**-0.2**	**-0.3**
	Output growth due to old products for non-product innovators	**5.4**	**8.0**	**3.9**	**-9.5**
	thereof for non-innovators	2.6	4.6	2.1	-7.3
	thereof for proc. innovators not being organ. innovators	0.5	0.7	0.4	-0.6
	thereof for organ. innovators not being proc. innovators	1.6	1.8	0.8	-1.1
	thereof for organisational and process innovators	0.7	0.9	0.6	-0.5
	Net contribution of product innovation for product innovators	**2.6**	**4.8**	**2.5**	**-2.3**
	thereof output reduction in old products	-5.8	-6.1	-6.5	-10.6
	thereof output increase due to new products	8.5	10.9	9.0	8.2
250+ employees	**Employment growth** - decomposed into:	**-3.0**	**3.7**	**-2.7**	**-8.5**
	General productivity trend in production of old products	**-6.9**	**-7.1**	**-8.1**	**3.7**
	Contribution of process and organisational innovation	**-2.0**	**-1.1**	**-0.4**	**-0.5**
	Output growth due to old products for non-product innovators	**2.2**	**3.0**	**1.3**	**-5.6**
	thereof for non-innovators	0.1	1.2	0.3	-3.2
	thereof for proc. innovators not being organ. innovators	0.2	0.2	0.2	-0.6
	thereof for organ. innovators not being proc. innovators	1.6	0.9	0.4	-1.1
	thereof for organisational and process innovators	0.4	0.7	0.4	-0.8
	Net contribution of product innovation for product innovators	**3.6**	**8.9**	**4.5**	**-6.1**
	thereof output reduction in old products	-12.0	-11.6	-13.9	-20.1
	thereof output increase due to new products	15.6	20.6	18.3	13.9

Source: CIS3, CIS4, CIS2006, CIS2008, CIS2010, Eurostat; authors' own calculation.

Note: Decomposition of the weighted-average two-year employment growth rate; the decomposition is based on the regression results presented in Table 4.6.

However, the decomposition analysis reveals a very different pattern for large firms. First, large firms experienced much higher employment losses than SMEs due to improvements in productivity during upturn, boom and downturn periods. Large firms realised efficiency gains of about 7 to 8% primarily as a result of the general productivity trend, i.e. selling unprofitable business units, mergers and acquisitions, learning effects or alike. Displacement effects of organisational and process innovation-induced productivity gains are much smaller, but still larger than in SMEs. Second, larger employment gains due to product innovation counteract the larger efficiency gains in large firms. Like for SMEs we find the net employment effect of product innovation to be pro-cyclical and positive in upturn, boom and downturn periods. In contrast to SMEs, the contribution of product innovation to average employment growth exceeds by far the one stemming from output growth for existing products of non-product innovators. Furthermore, employment creation due to demand growth for new and old products is not sufficiently high to outweigh employment losses due to efficiency gains in upturn and downturn periods. Third, the most striking result concerns the recession period. In contrast to SMEs, among the group of large firms non-product innovators perform better in terms of employment growth than product innovators (-5.6% vs. -6.1%). That is, we do not find large firms to be more resilient to economic crises. One explanation could be that large firms possess comparative advantages generating process innovations whereas small firms benefit relatively more from product innovation (Cohen and Klepper, 1996). Hence, large firms have a stronger incentive to invest in process innovation. The focus on process innovation relative to product innovation might be even stronger in recession periods due to lower product demand and increased competition based on costs and prices (Spiegel and Stahl, 2014).

4.6 Conclusion

This chapter is the first to examine the effects of different types of innovations on employment growth over the business cycle. A special focus is devoted to the question whether innovations can be regarded as a means to become more resilient to economic crises. Despite the literature argues that employment impacts of innovation crucially depend on product demand-driven effects, there is no firm-level evidence on this question yet. We analyse the labour-creating and labour-destructing effects of product, process and organisational innovations over the business cycle using the structural model developed by Harrison et al. (2014). We estimate the model with CIS firm-level data from 26 European countries covering the period from 1998 to 2010. In total, our sample includes more than 200,000 firm-year observations of the manufacturing sector. To account for business cycle heterogeneity in the effects of innovation on employment, we split our estimations into the four phases (upturn, boom, downturn, recession) of a business cycle based on country-specific GDP growth rates.

Descriptive statistics already reveal an interesting pattern: Average employment growth is pro-cyclical for each type of innovators and for non-innovators. However, employment grows much faster for innovators than for non-innovators in each phase of a business cycle. This gap in employment growth between innovators and non-innovators widens during downturn and recession periods.

To estimate the employment growth effects of innovation, we rely on IV estimations using a sensible identification strategy to correct for potential measurement error. In addition, we quantify the actual contributions of different types of innovators and non-innovators to average employment growth by performing a decomposition analysis. Our empirical analysis reveals four major findings. First, the net employment growth effect of product innovators is strictly pro-cyclical. This effect is positive during upturn, boom and downturn periods and indicates the labour-creating effect to exceed the labour-destructing effect of product innovations. The reverse pattern emerges in recessions in which the net employment growth effect turns negative, indicating average labour-destruction. Second, product innovators are more resilient to recessions than non-product innovators. Indeed, when facing negative economic growth, product innovators on average cut jobs. However, the level of job destruction is only modest compared to the job destruction in firms that have not implemented any product innovations between t and t-2. Third, we find resilience only in SMEs but not in large firms. Fourth, on average, process and organisational innovations particularly reduce the innovators' labour demand during upturn and downturn periods. That is, the innovators implemented new processes and business practices, respectively, that enhanced the production efficiency at the cost of reduced labour demand.

Our results have important policy implications. First, we show the strong and positive linkage between innovation and employment which supports a stronger alignment between these two policy fields. Second, the employment-preserving effect of product innovations during recessions is a strong argument for a counter-cyclical public support of product innovation activities. Increasing the public funding for innovation activities during a recession may help firms to stabilize expectations and overcome potential financing constraints. However, the precise timing of such measures can be cumbersome. Automatic stabilizers in public support schemes such as an automatic increase in the tax credit for R&D in a recession may be an answer to the timing problem. In times of a recession, firms may have already downsized their R&D personnel or other innovation-related expenditures before a government adopts and actually pays the counter-cyclical innovation support.

Our study is subject to some limitations. First, the lack of firm identifiers does not allow us to analyse employment growth effects for the same firm over time. However, we can split the observed firms into the respective business cycle phases. This allows us to analyse the employment growth dynamics for different types of innovators and non-innovators for specific growth periods. Second, the correct identification of the gross effect of process and organisational innovation actually depends on the availability of data on firm-level price changes of old products. This type of data is generally not available in firm-level data sets. Therefore, we use industry-level price growth rates as proxy variable. Larger deviations between firm- and industry-level prices may bias our results. Third, due to lack of firm-level price data we are also not able to estimate the net employment effect of process and organisational innovations. That is, we only get an estimate for the labour destruction due to productivity enhancements but not for the potentially induced labour creation due to price reductions. Fourth, authors have argued that organisational innovation is a fuzzy concept and difficult to define (Lam, 2005; Armbruster et al., 2008). Hence, organisational innovation is more likely to be subject to potential mismeasurement. We use data from the harmonised CIS that includes clearly defined questions about organisational innovations. Still, survey respondents may be less sure about the meaning of "organisational innovations" compared to product or process innovation.

Despite the limitations, our analysis draws a positive picture of the ability of innovation to create new employment. This puts our results in some contrast to other recent research, which points to potential negative effects of new process and automatization technologies on employment (see e.g. Frey and Osborne, 2013; Brynjolfsson and McAfee, 2014). It may be that potential losses from innovation are more visible than the potential benefits of new technologies from today's perspective. There may also be a tendency to underestimate benefits and overestimate losses from technological change. The most important lesson policymakers can learn from our results is that innovations create new jobs particularly during recessions.

4.A Appendix

Table 4.A.1: Country coverage and distribution of the CIS survey waves

Country	Country	Wave					Manufacturing	
		1	2	3	4	5	N	%
Belgium	BE	+	-	-	-	-	652	0.3
Bulgaria	BG	+	+	+	+	+	26,716	13.2
Cyprus	CY	-	-	+	+	+	1,217	0.6
Czech Republic	CZ	+	+	+	+	+	11,722	5.8
Germany	DE	+	-	-	+	+	5,501	2.7
Denmark	DK	+	+	(+)	-	-	748	0.4
Estonia	EE	+	+	(+)	+	+	3,631	1.8
Spain	ES	+	+	(+)	+	+	38,816	19.2
Finland	FI	+	-	-	-	-	900	0.4
France	FR	+	+	-	+	+	26,559	13.2
Greece	GR	+	+	(+)	-	-	1,318	0.7
Croatia	HR	-	-	-	-	+	1,212	0.6
Hungary	HU	+	+	(+)	+	+	7,145	3.5
Iceland	IS	+	+	-	-	-	315	0.2
Italy	IT	+	+	-	+	+	25,929	12.9
Lithuania	LT	+	+	(+)	+	+	2,564	1.3
Luxembourg	LU	+	+	(+)	+	+	581	0.3
Latvia	LV	+	+	(+)	+	+	2,201	1.1
Malta	MT	-	-	(+)	+	-	224	0.1
Netherlands	NL	-	-	-	+	+	3,445	1.7
Norway	NO	+	+	-	-	+	3,883	1.9
Portugal	PT	+	+	(+)	+	+	9,576	4.7
Romania	RO	+	+	+	+	+	18,477	9.2
Sweden	SE	+	-	-	-	+	3,035	1.5
Slovenia	SI	-	+	-	+	+	2,022	1.0
Slovakia	SK	+	+	(+)	+	+	3,302	1.6
Total		21	18	4 (15)	18	20	201,691	100

Source: CIS3, CIS4, CIS2006, CIS2008 and CIS2010, Eurostat; authors' own calculation.

Note: Values in parentheses reflect that the data for the respective country is available but not the organisational innovation indicator.

Table 4.A.2: Distribution of CIS sample by industry

Industry	Variable	Nace Rev. 1.1.	Nace 2	Total	
				N	%
Food / beverages / tobacco	FOOD	15-16	10-12	28,860	14.31
Textile / wearing apparel / leather	TEXT	17-19	13-15	28,937	14.35
Wood / paper / printing	WOOD	20-21, 22.2-22.3	16-18	22,820	11.31
Chemicals	CHEM	24	20-21	10,698	5.30
Rubber / plastics	PLAS	25	22	11,021	5.46
Non-metallic mineral products	NONM	26	23	11,493	5.70
Basic and fabricated metals	BASM	27-28	24-25	28,000	13.88
Machinery	MACH	29, 33.3	28, 33	20,518	10.17
Electrical engineering	ELEC	30-32, 33.2, 33.4-33.5	26-27	14,973	7.42
Vehicles	VEHI	34-35	29-30	9,548	4.73
N.e.c.	NEC	36, 33.1	31-32	14,823	7.35
Total				201,691	100

Source: CIS3, CIS4, CIS2006, CIS2008 and CIS2010, Eurostat; own calculation.

Note: Until CIS2006 the industry classification was based on NACE Revision 1.1, since CIS2008 NACE Revision 2 has been used as industry classification system.

Table 4.A.3: Distribution of the sample's different firm groups

Firm groups	Total
	%
Non-innovators	50.5
Product innovators	27.0
Process innovators	11.1
Organisational innovators	32.1
Small firms	77.0
Medium-sized firms	18.8
Large firms	4.2
Firms pertaining to a domestic enterprise group	81.6
Firms pertaining to a foreign enterprise group	13.0
Firms not pertaining to an enterprise group	5.4

Source: CIS3, CIS4, CIS2006, CIS2008 and CIS2010, Eurostat; authors' own calculation.
Note: Weighted statistics; process innovators refer to firms that implemented only process innovations (PC) during t and t-2.

Table 4.A.4: Distribution of the CIS sample by business cycle phase

Observation period	Business cycle phases			
	Upturn	Boom	Downturn	Recession
1998-2000	23,756	12,420	3,868	0
2002-2004	41,767	785	845	0
2004-2006	0	2,434	10,682	0
2006-2008	0	224	51,784	0
2008-2010	1,945	0	0	51,181
Total	67,468	15,863	67,179	51,181
in %	33.45	7.87	33.31	25.38

Source: CIS3, CIS4, CIS2006, CIS2008 and CIS2010, Eurostat; authors' own calculation.

Table 4.A.5: Sales growth due to new and old products by innovator and business cycle phase, in %

Firm type	Business cycle phase	Total	Old products	New products
All firms	Upturn	11.2	2.4	8.8
	Boom	16.4	4.4	12.1
	Downturn	14.1	4.8	9.3
	Recession	-10.4	-19.0	8.6
Innovators	Upturn	13.6	-4.4	18.0
	Boom	17.3	-2.4	19.7
	Downturn	16.4	-4.0	20.4
	Recession	-8.2	-25.9	17.7
Non-innovators	Upturn	8.9	8.9	0.0
	Boom	15.0	15.0	0.0
	Downturn	12.2	12.2	0.0
	Recession	-12.5	-12.5	0.0
Process innovators	Upturn	14.0	14.0	0.0
	Boom	17.4	17.4	0.0
	Downturn	16.3	16.3	0.0
	Recession	-9.1	-9.1	0.0
Product innovators	Upturn	14.8	-22.7	37.5
	Boom	17.8	-15.3	33.1
	Downturn	16.4	-19.7	36.1
	Recession	-7.1	-37.0	29.9
Organisational innovators	Upturn	14.1	-2.1	16.2
	Boom	17.8	-1.2	19.0
	Downturn	17.7	-1.6	19.4
	Recession	-8.0	-24.4	16.4

Source: CIS3, CIS4, CIS2006, CIS2008 and CIS2010, Eurostat; authors' own calculation.
Note: Weighted statistics; non-innovators did not introduce product, process or organisational innovations during t and t-2; "Process innovators" refers to pure process innovators (PC).

Chapter 5

Employment Growth and Counter-Cyclical R&D Investment: A Comparison between German and US Start-Ups[54]

5.1 Introduction

There is large consensus among policymakers and economic researchers as to the importance of start-ups for economic growth (Carree and Thurik, 2010). In Europe, start-ups have come into a wide focus again during the most recent recession period of 2008/2009 (EC, 2013). As part of the Europe 2020 Strategy – a Europe-wide growth plan initiated in 2010 – the European Commission (EC) intends for Europe to become more entrepreneurial. The underlying motivation includes both the start-ups' innovative potential and the related potential for job creation. In this respect, Veugelers (2009) and Biosca (2010) state that a more start-up-oriented Europe would be capable of reducing the productivity gap relative to the US. The US-American start-ups grow faster than the European start-ups (EC, 2013). After all, the US economy is one of the most entrepreneurial economies in the world. Its success and robustness is largely attributable to its flexibility and dynamics triggered by new firm foundations (Decker et al., 2014). Haltiwanger et al. (2013) even find evidence that young firms are responsible for almost all the US net job creation. Nonetheless, there has been a concerning development regarding the new US firms' capability of job creation. Reedy and Litan (2011) show a downward trend in both the average firm size at birth and the average employment growth during the early years after birth. This negative development has even been reinforced by the recession period of 2008/2009 (Haltiwanger et al., 2011). These exemplary developments emphasise that accurate information about the performance and the sustainability of new firms is essential to initiating public and private programs that strengthen the development of new firms.

Against this backdrop, we analyse the employment growth effects of start-ups' R&D investment and its business cycle dependency for the USA and Germany, the largest economy

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in Europe. In particular, our target is to investigate whether or not higher R&D investment during the 2008/2009 recession could increase the start-ups' job creation in 2010. The innovative power is one of the key elements that make start-ups indispensable for technological change and aggregate growth. For instance, Henderson and Clark (1990) argue that new firms – compared to established ones – may invest in new technology to exploit its potential more effectively. In a similar line of reasoning, Akcigit and Kerr (2015) emphasise that established firms tend to invest in R&D to improve their existing products, whereas new firms invest to aspire technological leadership. Despite their economic importance and political relevance the link between innovation and new firm growth is still underresearched (Koellinger and Thurik, 2012; Coad et al., 2013a). For instance, only a few empirical studies go beyond the cross-sectional horizon, which is necessary as newly founded firms exhibit strong dynamics during the first years of existence. With our chapter, we contribute to the literature in three respects. First, we provide evidence as to the annual job creation related to start-ups' innovation activities, measured by firm-level R&D investment indicators. Second, we examine the employment growth effects over the business cycle to capture the cyclical dependency of R&D investments. In particular, we investigate whether or not start-ups could gain from higher job creation if they invested more in R&D during the 2008/2009 recession. Third, by analysing comparable data sets of two different countries over time, we at least partly circumvent the problem a large share of the empirical start-up literature suffers from, i.e. the lack of comparability of the results.

In this chapter, we use longitudinal random samples of German and of US-American start-ups that were followed over eight years. The US data is provided by the confidential, restricted-access version of the Kauffman Firm Survey (KFS). The KFS collected annual information of almost 5,000 start-ups that were born in 2004. To analyse the employment effects of German start-ups, we use the KfW/ZEW Start-Up Panel (SUP). The SUP actually includes annual information on 15,300 start-ups that were founded between 2005 and 2012. For reasons of comparability, our SUP sample only includes the 2005 cohort, which covers information of about 1,800 start-ups. Our final samples include 7,291 (KFS) and 2,386 (SUP) firm-year observations and cover the periods of 2004-2011 (KFS) and 2005-2012 (SUP), respectively. We use two different R&D investment indicators: (i) the level of R&D investment over the number of full-time equivalents as well as (ii) the one-year difference of this R&D intensity to measure the employment effect of a direct increase of R&D investment. To account for business cycle effects, we interact the two R&D indicators with country-specific GDP growth rates. In addition, we control for cyclical industry differences by using industry-specific gross value added (GVA) growth rates to construct the interaction terms. As manufacturing firms are the most important R&D performers, we also estimate our models for firms of the manufacturing sector only.

By using pooled OLS, we find that higher R&D investment has a positive effect on start-ups' job creation. This positive effect holds for both the US and the German start-ups, even though the effect is not significant for the US start-ups. With respect to business cycle effects, our results indicate that counter-cyclical R&D investment is an effective way to increase employment growth. However, this counter-cyclical effect is only significant for manufacturing firms. There is a fundamental difference between the results of the German and the US start-ups. Whereas in Germany a higher level of R&D intensity during the recession is significantly related to higher subsequent employment growth, in the US it is the annual difference of the R&D intensity. This country difference implies that an industry perspective may be more important in Germany than a firm perspective. That is, a higher general level of R&D investment during recessions could induce employment growth but not if the firms increased their R&D investment, on average. In contrast, the direct increase in R&D investment may be more desirable for US-American start-ups during recessions. Even though the perspectives may be different, the overall conclusion of our analysis is that start-ups will be rewarded for R&D investment during recessions.

The chapter is organised as follows. The next section reviews the relevant theoretical and empirical literature, while Section 5.3 presents and discusses the data. Section 5.4 presents the empirical approach and the results. The last section concludes.

5.2 Theoretical background and previous empirical results

5.2.1 New firm growth and innovation

The majority of research on firm growth and innovation activities focusses on small and medium-sized enterprises (SMEs) or on large firms. Influential papers as Evans (1987) and Haltiwanger et al. (2013) show that firm growth rates significantly differ across firm size and firm age. In this vein, Acemoglu et al. (2013) show for US manufacturing firms that small and young firms exhibit a higher R&D intensity and higher sales and employment growth than large and old firms. With the following section we intend to give some indication why particularly new firms' innovation activities can be expected to increase firm growth.

The basic mechanism that links innovation activities to new firm growth evolved from the Schumpeterian endogenous growth models (Aghion and Akcigit, 2015). According to that paradigm, firms are forward-looking and profit-seeking. They invest in research and development (R&D) as much as they need to implement innovations. Successful innovations improve the firms' product quality (Segerstrom et al., 1990; Grossman and Helpman, 1991) and the firms' production efficiency (Aghion and Howitt, 1992), respectively. In both cases the successful innovators will gain monopoly rents. These first-generation Schumpeterian models predict that new firms are the innovative drivers. More recent models not only allow established firms to innovate as well but also incorporate multiple forms of innovations. For instance, Acemoglu and Cao (2015) assume that established firms can conduct R&D activities that would enhance their productivity and profitability. In contrast, new firms invest in "radical" R&D that allows them to replace the established firms. In a similar model, Akcigit and Kerr (2015) differentiate between internal and external innovation. The former innovation type is linked to incremental improvements performed by established firms. The latter innovation type refers to innovation activities aiming at obtaining technology leadership. External innovation can be undertaken by new firms as well as by established firms. As Akcigit and Kerr (2015) do not have any direct information to quantify external vs. internal differences, they use the NBER Patent Database to create internal and external patent citation indicators as proxies. Akcigit and Kerr (2015) match the patent data with the Longitudinal Business Database to obtain firm information. In line with the data, their model predicts smaller firms to have a disproportionate higher share of patents with external citations than larger firms. Furthermore, new firms have a higher average external citation count than established firms. Akcigit and Kerr's interpretation is that small and new firms have a comparative advantage for achieving major inventions.

Klepper (1996) uses an industry evolution framework to develop a model that emphasises the differences in firms' innovative capabilities and the importance of firm size in appropriating the returns from innovation. His model predicts that the larger firms are the more they spend for process-related R&D relative to smaller firms. This means, smaller firms – compared to larger firms – tend to be more focused on new product development than on productivity improvements. By using US data from the FTC's Line of Business Program and US patent data, Cohen and Klepper (1996) find evidence for this prediction. They also have a very similar interpretation for this finding as Akcigit and Kerr (2015) have, i.e. small firms have a comparative advantage in generating major innovations. In a recent study, Criscuolo et al.

(2012) employ a matching estimator on UK firms and find that new firms are more likely to introduce product innovations than established firms. This effect, however, only occurs in service rather than manufacturing firms. More importantly, they find evidence for new firms having introduced product innovations to generate higher innovative sales than established firms. Their results at least partly support the implications made by the models described earlier in that new firms' innovation activities tend to be rather product-oriented.

These models and findings give some intuition of why start-ups have a considerable firm growth potential related to innovative investment. Another explanation refers to the concept of absorptive capacity (see Cohen and Levinthal, 1990). It represents the firms' ability to learn and to exploit knowledge. According to Kreiser (2011), start-ups are more dependent on their ability to fully utilise resources than other firms. Knowledge is a key determinant in start-ups' performance, a lack of absorptive capacity would lower the firms' ability in seizing new opportunities and evaluating them appropriately, respectively (Zahra and George, 2002; Engelen et al., 2014). Prior research shows R&D investment to be a frequently used indicator to measure firms' absorptive capacity (see e.g. Tsai, 2009). This means, if firms invested in R&D they would be potentially more able to innovate and to absorb knowledge from the external environment more effectively (Rosenberg, 1990; Criscuolo et al., 2012). In principle, start-ups have a weak resource base, building up absorptive capacity by investing in R&D should increase the start-ups' performance relative to start-ups that do not invest in R&D (Garnsey, 1998; Rosenbusch et al., 2011). In contrast, it may be even possible that higher R&D investment does not pay off. It is a risky investment and start-ups do not have a large product portfolio that could absorb investment failures. An additional related explanation for positive growth effects takes the new firms' flexibility into account. As new firms lack established routines they can more easily adapt to environmental changes (March, 1991; DeCarolis, 2003). In this sense, if new opportunities opened up, they would not have to overcome rigidities inherent to established routines (Hannan and Freeman, 1984; Rosenbusch et al., 2011). For instance, Jovanovic and Rousseau (2014) develop an AK type model and show that small and young firms respond positively to technological change, whereas large and old firms respond negatively to it. This asymmetric response is triggered by implementation costs that emerge in old and large firms to make the "new" capital compatible to the "old" capital.

According to the theoretical considerations, we would expect a positive effect of the new firms' innovation activities on firm growth. Previous empirical results as to the growth of new firms largely support the growth-inducing effects of innovation.[55] Deeds (2001) investigates the relationship between R&D intensity and market value added of 80 new biotechnology firms in the US. He gathered data from the Center for Research in Security Prices (CRSP), The Center for Research Planning (CRP) and the firms' IPO prospectus. R&D intensity is measured as the average percentage of total expenditures spent on the R&D process during the last three years. He finds an increase in R&D intensity to be associated with a higher market value added and concludes that a strategic focus on the development of products by new ventures creates entrepreneurial wealth. A similar study is performed by Dowling and McGee (1994). Instead of new biotechnology firms, they examine potential growth effects of R&D investment for 52 new ventures of the telecommunications equipment manufacturing industry. They use data from the IPO registration statements and cover the period of 1980-1988. Whereas firm growth is measured as a three year compounded average sales growth

[55] We only describe empirical results for new firms as these are comparable to our unit of observation. With regards to potential growth effects of innovation of SMEs see e.g. Roper (1997), Freel (2000), Freel and Robson (2004), Hölzl (2009) and Capasso et al. (2015). Research on innovation and firm growth of all size classes can be found in e.g. Hall (1987), Del Monte and Papagni (2003), Coad and Rao (2008, 2010), Hölzl and Friesenbichler (2010); Falk (2012), Garcia-Manjon and Romero-Merino (2012), Harrison et al. (2014) and Segarra and Teruel (2014).

rate, R&D investment is proxied by the three-year average ratio of firms' R&D expenditures relative to their sales. Like Deeds (2001), Dowling and McGee (1994) find evidence for a positive relationship between R&D and firm growth. Furthermore, their results indicate first mover advantages based on R&D investment. A recent study by McKelvie et al. (2013) also seeks to disentangle the relationship between new firms' innovative activities and subsequent sales growth. The authors identified a sample of new Swedish firms of the knowledge-intensive sectors by using information from Statistics Sweden. New firms are defined as nine-year-old firms or younger. After the identification, they sent a questionnaire created on their own to the firms' CEOs, which allowed them to finally gather information of 282 new firms. In contrast to the two previously described studies, McKelvie et al. (2013) rely on three different indicators measuring firm innovation directly, i.e. (i) formal R&D (ii) (radical) product innovator, (iii) percentage of sales with new products. The indicators (i) and (ii) are the result of factor analyses and measure whether or not the firms have a strong R&D and (radical) product innovation focus, respectively. Whereas a strong R&D-orientation does not increase the firms' sales growth, McKelvie et al. (2013) find weak evidence for growth-inducing effects of product innovators. In addition, innovation success is strongly positively related to sales growth.

Most closely related to our analysis is the research undertaken by Stam and Wennberg (2009), Czarnitzki and Delanote (2012) and Coad et al. (2013a). For their analysis on employment growth effects of innovation, Stam and Wennberg (2009) use information from the Dutch "Start-up panel: cohort 1994", a representative sample of Dutch start-ups founded in 1994. They focus on the first six years of the firms' life and restrict their analysis on surviving firms only. The authors measure innovation three-fold: (i) as an R&D dummy variable, (ii) as the percentage of labour time spent on R&D and (iii) as an indicator that assigns whether a firm has been involved in developing new products or not. The dependent variable is a firm-specific six-year employment growth rate. Based on 629 observations, Stam and Wennberg (2009) cannot find a general significant effect for R&D and new product development. A positive significant effect for R&D emerges for high-growth as well as for high-tech firms. New product development is only significant for high-tech firms and only when interacted with R&D. Czarnitzki and Delanote (2012) examine the annual sales and employment growth effects of young innovative companies for the period of 2001-2008. They use the Flemish part of the Community Innovation Survey (CIS) and the Eurostat/OECD R&D survey and have 7,888 (sales growth) and 6,110 (employment growth) final observations, respectively. Young innovative companies (YIC) are defined as firms being younger than six years, having less than 250 employees and having a ratio of R&D expenditures per sales of more than 15%. Pooled OLS results show that YICs grow faster both in terms of sales and employment compared to other firms. Additional quantile regressions strengthen that result and exhibit an even more superior growth performance of YICs among the top 30% of the highest-growing firms. A recent paper by Coad et al. (2013a) explores the relationship between firm growth, innovation and firm age for Spanish firms that were observed between 2004 and 2010. To conduct their empirical analysis, the authors use information from the Technological Innovation Panel (PITEC). They split their estimation sample into young firms (< 15 years, 4,797 observations) and old firms (> 30 years, 5,793 observations). Firm growth is measured by three different indicators: (i) the first-difference of the log of firm sales, (ii) the first-difference of the log firm productivity growth and (iii) the first-difference of the log of firm employment. Innovation is measured as the log of R&D expenditures per sales. In line with Czarnitzki and Delanote (2012), the authors rely on quantile regressions. The results for young firms indicate a positive relationship between R&D and the firm growth measures. Similar to Stam and Wennberg (2009) and Czarnitzki and Delanote (2012), innovation becomes more important and more significant for high-growing firms.[56] For instance, higher R&D effort significantly increases the young firms' employment growth only for firms that belong to the 25% and 10% highest-growing firms, respectively.

The studies just discussed may investigate the innovation-growth relation of new firms but they are very heterogeneous, e.g. in the way firm innovation is measured, which specific industries are covered and whether independent start-ups/new firms were observed or not. Even more important, none of these studies use a comparable definition of "young" or "new", which makes it difficult to compare the results. Even though Deeds (2001) and Dowling and McGee (1994) use the terms "new firms" and "start-ups", respectively, they do not give any information on the firms' age or the firms' founding year. McKelvie et al. (2013) define new firms to be younger than ten years, Czarnitzki and Delanote (2012) refer to young firms as firms not being older than five years and Coad et al. (2013a) set the threshold for "young" at a firm age of (younger than) 15. By intermingling firms of different age cohorts and labeling them as "new" or "young", these papers disregard the significant underlying firm dynamics of newly founded businesses. For instance, the new firms' exit rate is particularly high during the first three years after foundation (see e.g. Mata and Portugal, 1994; Wagner, 1994; Geroski, 1995; Ejermo and Xiao, 2014). However, Czarnitzki et al. (2012) and Coad et al. (2013a) implicitly partly compensate for that drawback by using quantile regressions at least if assumed that fast-growing firms are the very young firms.

Nevertheless, if policymakers and researchers want to understand the factors influencing new firm growth then it may be the best approach to examine firms differentiated by their age and their founding year. In this sense, Stam and Wennberg (2009) is the only study on new firm growth and innovation relying on that approach. Unfortunately, it is not very clear to us why they only cover a six-year period, even though the "Start-up panel: cohort 1994" covers at least ten years of observations. Our analysis is close to their approach in that we rely on start-up survey data allowing us to examine specific firm cohorts over the first years of their existence. Significant differences are that we investigate annual growth effects of R&D investment, consider business cycle effects and compare the effects of two different countries.

5.2.2 Innovation and the business cycle

The following stream of literature has not yet examined the role of new firms' innovation activities over the business cycle. Therefore, the following section will only present the most important concepts and results for established firms.

The literature on the relationship between the business cycle and innovation has largely focused on innovation input. According to early research, firms shift more resources to productivity-enhancing activities, as for instance R&D investment, during recessions than during growth periods. This counter-cyclical pattern arises because the opportunity costs of long-term investment – in terms of forgone output – are lower compared to short-term capital investment during recessions (see e.g. Bean, 1990; Gali and Hammour, 1991; Saint-Paul, 1993; Aghion and Saint-Paul, 1998). The opportunity cost effect has more recently been neglected because it implies firms to have the same or even stronger financial capabilities to finance innovation projects during recessions. Due to credit market imperfections, conducting innovation activities mainly depends on the firms' cash flow (see e.g. Hall, 1992; Himmelberg and Petersen; Harhoff, 1998; Mulkay et al., 2001; Rafferty and Funk, 2008). Therefore, it seems unlikely that more financial resources can be raised to intensify firms' innovative effort during recessions, i.e. during periods of decreasing cash flow. This liquidity

[56] The pattern is a bit different for old firms. In particular, R&D investment has no significant effect on employment growth for old firms across all quantiles.

constraint would cause pro-cyclical R&D investment. The liquidity constraint argument could explain that Wälde and Woitek (2004) who observe information on G7 countries during 1973 and 2000 find evidence that R&D investment varies pro-cyclically over time.[57] By using data from the National Science Foundation (NSF) and Compustat, Barlevy (2007) shows for the period of 1958-2003 that R&D investment is pro-cyclical as well. In addition, he builds a Schumpeterian endogenous growth model and predicts R&D to be pro-cyclical, even though it is not socially optimal. He assumes R&D investment and the implementation of innovation to occur contemporaneously because firms are impatient. This means, the timing of R&D determines the timing of the implementation. As innovators are assumed to be profit-seeking and imitators are expected to emerge immediately after a new idea has been discovered, innovators shift their innovation activities to upturn periods.

More recent contributions find asymmetric effects of R&D investment. Ouyang (2011) investigates the opportunity cost hypothesis regarding the cyclicality of R&D investment. She uses sector data of 20 US manufacturing industries covering the period of 1958 and 1998 and finds R&D to be pro-cyclical in general. In addition, by using more aggregated indicators her results disclose an asymmetric response of R&D. That is, a positive demand shock causes R&D expenditures to decrease due to rising opportunity costs, whereas a negative demand shock decreases R&D investment due to liquidity constraints. Despite this asymmetric drift, Ouyang (2011) argues that the liquidity constraint is the key determinant in explaining the general result of pro-cyclical R&D investment. Aghion et al. (2010) could also find asymmetric cyclical effects of long-term investment.[58] They use data of 21 OECD countries that were observed between 1960 and 2000. According to their results, the ratio between long-term investment and total private investment is pro-cyclical in countries that have sufficiently tight credit markets. Aghion et al. (2012) use a sample of 13,000 French firms that were observed during the period 1993-2004. The authors' results show that credit-constrained firms increase their R&D expenditures during cyclical upturns compared to non-constrained firms. This finding supports the pro-cyclicality for credit-constrained firms. This relationship, however, turns to be counter-cyclical in the case of non-constrained firms.[59]

In line with the pro-cyclicality of R&D investment, Geroski and Walters (1995) find evidence for the pro-cyclicality of innovation output. They investigate UK firms over the period 1948-1983 and find that cyclical variations Granger cause the total number of innovations and the number of patents. Furthermore, the authors show that the innovation activities tend to cluster during boom periods. In his model, Shleifer (1986) focusses on the timing of the commercialisation of innovation rather than on R&D investment. Instead, he assumes inventions to be exogenously developed and to arrive at a constant rate. Similar to Barlevy (2007), innovators are profit-seeking and time the implementation of innovations to maximise the profit. Due to entering imitators that eliminate all profits, the innovators delay the implementation until a boom emerges. Francois and Lloyd-Ellis (2003) endogenize innovation in Shleifer's model. In their model, innovative effort produces inventions that can be stored and be held secret. This allows a strategic delay of the implementation of innovations. During recessions, the innovators do delay and wait until the boom arrives but they also increase their innovative effort. When the boom arrives, the innovators will gain their monopoly profits and will shift their resources from innovative effort to production. In a later paper, Francois and Lloyd-Ellis (2009) predict R&D and the implementation to be pro-cyclical but occurring at different phases. They assume R&D to produce ideas that first have to be incorporated in products before they can be implemented as an innovation. According to

[57] For further evidence on the pro-cyclicality of R&D see e.g. Fatas (2000) and Comin and Gertler (2006).

[58] Aghion et al. (2010) do not use R&D investment but long-term investment (a proxy for growth-enhancing investment).

[59] By using Slovenian and Spanish firm-level data Bovha-Padilla et al. (2009) and López-Garcia et al. (2012), respectively, follow the approach of Aghion et al. (2012) and find support for Aghion et al.'s (2012) results.

the model, the value of the ideas is highest during the expansion period which follows an implementation boom period. Hence, R&D effort is maximised during expansions. During recessions, when the demand slows down, the innovators reduce their R&D activities and increase their search effort so that they can match applications with the ideas. The search effort reaches its peak before the implementation boom can be expected. Fabrizio and Tsolmon (2014) take the approaches of Shleifer (1986), Francois and Lloyd-Ellis (2003, 2009) and of Barlevy (2007) directly into account when empirically investigating the pro-cyclicality of R&D investment and innovation. Their analysis is based on Compustat, NBER Patent Data, the Carnegie Mellon survey (CMS) and the NBER Manufacturing and Productivity Database and covers the years 1975-2002. The R&D indicator is measured as the first-difference of the log of R&D expenditures. Innovation is measured as the number of patents. Fabrizio and Tsolmon (2014) also include a measure indicating industry-level patent effectiveness to test whether the imitators' threat leads to more pro-cyclicality or not. With regards to the separate timing of R&D investment and innovation, the authors include an indicator that measures the speed with which innovations are introduced in the firms' focal industry. Their findings are consistent with the pro-cyclical pattern of R&D investment and innovation. According to their results, the timing of innovation is more pro-cyclical the stronger the threat of imitators in the firms' focal industry is. The pro-cyclicality of innovation, however, does not depend on the industry-level speed of the introduction of innovations. In contrast, a higher speed leads to more pro-cyclicality of R&D investment. Their results suggest two things: (i) firms shift the implementation of innovations to growth periods and (ii) if inventions did not lose in value very quickly firms would tend to shift R&D investment to downturn periods.

Based on these findings, we would expect that start-ups conduct R&D investment during recession periods as well. Furthermore, they probably shift the market introduction of innovations to boom periods to match the positive market demand. Hence, R&D investments during recessions may lead to more innovations during the subsequent boom period, which is likely to create more jobs than in case the R&D investment occurs in economic booms.

5.3 Data

5.3.1 Sources

5.3.1.1 Kauffman Firm Survey (USA)

To analyse the employment growth effects for the US-American start-ups we use the Kauffman Firm Survey (KFS). The KFS is the largest longitudinal study of new firms in the USA ever embarked upon. The panel was commissioned by the Ewing Marion Kauffman Foundation and was conducted every year from 2005 to 2012 by Mathematica Policy Research Inc. (MPR). The panel of start-ups was created by using a random sample from Dun & Bradstreet's (D&B) data base list of new firms started in 2004.[60] A firm started in 2004 was defined as a new, independent firm that was created by at least one person, the purchase of an existing firm, or the purchase of a franchise. The stratification criteria were defined by industrial technology categories (based on industry designation) and the gender of the founder/s.[61]

The first survey wave was conducted between July 2005 and July 2006 and has collected information on 4,928 firms that were founded in 2004. These start-ups were surveyed every year until 2012. They could complete the questionnaire online or via computer-assisted

[60] Dun and Bradstreet is the world's largest provider of business information.

[61] For detailed information on the survey design and the sampling process see Robb et al. (2009) and Ballou et al. (2008).

telephone interviews. The data contains detailed information on (i) entrepreneurial characteristics (e.g. age, gender, race, education, work and prior start-up experience), (ii) finance characteristics (e.g. amount of investments, financing sources and structure) and (iii) basic firm characteristics (e.g. sales, employees, profits, R&D expenditures).

For our analysis, we rely on the KFS confidential data set that is available to researchers through a remote access data enclave provided by the National Opinion Research Center (NORC). Unfortunately, information on R&D investment is only available from 2007 on, which restricts our estimations to the period of 2007-2011. The total size of our US sample includes 7,291 firm-year observations.

5.3.1.2 KfW/ZEW Start-Up Panel (Germany)

We use data from the first six survey waves (2008-2013) of the KfW/ZEW Start-Up Panel (SUP). This is a unique panel data set on newly founded firms in Germany. The panel was established in 2008 by the Centre for European Economic Research (ZEW), the KfW Bankengruppe (a large German government-owned bank) and Creditreform (Germany's largest credit rating agency). In 2008, a stratified random sample was drawn from the population of all new firm foundations in Germany, which have been recorded by Creditreform. A new firm was defined as new, legally independent firm that was created by at least one person. The stratification criteria were the year of foundation, the focal industry and whether the firm had received financial support by the KfW or not.[62]

The first survey wave was conducted in the middle of 2008 and has collected annual information on about 5,500 firms that were founded between 2005 and 2007. In addition, from 2009 on the SUP has been expanded by a random sample of new German firms every year. The newly added firms must have been three years of age or younger when they were interviewed for the first time. Each responding firm has been annually surveyed by computer-assisted telephone interviews and has been followed by not more than eight years. In total, the first six waves of the SUP include 15,300 German start-ups. Just like the KFS, the SUP contains detailed information on entrepreneurial, finance and basic firm characteristics.

We restrict our German sample to the 1,800 firms that were founded in 2005. This allows us to be "as closest as possible" to the KFS firms that were founded only one year earlier. Our analysis focusses on the most recent recession period, so we wanted the US and German start-ups to have about the same age. The SUP covers R&D investment information only from 2007 on as well. This restricts our estimations to the period of 2007-2012. The total size of our German sample includes 2,386 firm-year observations.

5.3.1.3 Differences between the KFS and SUP survey designs[63]

One major contribution of our analysis to the literature is that we estimate the same models for two different but still comparable countries. The validity on the comparability of our results depends on the similarity of the two data sets. Fryges et al. (2010) explicitly mention the suitability of the SUP regarding comparative research with the KFS. According to them, the design of the SUP and KFS is similar "[…] in that it tracks newly founded firms over more than six years and also focusses on firm strategies, financing, innovation and labour demand" (Fryges et al., 2010; p. 129).

[62] More detailed information on the survey design and the SUP's sampling process is provided by Fryges et al. (2010).

[63] Please note: We can only use both data sets separately. Confidentiality reasons do not enable us to pool the data sets as we only have remote access to the KFS data and do not have a copy of them. Hence, we cannot conduct direct sample comparisons as, for instance, matching the firms of both countries with each other to have a really comparable firm sample.

However, there are notable differences in the survey designs. First, the KFS' first wave was conducted about one to two years after the founding year of 2004. The SUP's first wave was conducted in 2008 with firms that had already survived about three years after foundation in 2005. This implies that the 2005 founded SUP firms may be more robust than the KFS firms. However, both estimation samples cover periods that start in 2007. Second, the KFS' industry-specific sampling strata were more aggregated (high-tech, medium-tech, non-tech) compared to the ten industrial sectors the SUP was stratified. However, both the SUP and the KFS intentionally oversampled high-tech industries. Third, those responsible for the KFS put a lot more effort in terms of manpower and financial resources into surveying the firms than the SUP equivalents. In particular, each successful participant received 50 USD every year. The project team sent several reminder letters/postcards/emails and even staff was trained in refusal conversion. This means that the response rate was higher for the KFS than for the SUP. However, our SUP sample is sufficiently large to be comparable with the KFS sample. Fourth, the SUP did not sample firms of the agricultural and mining sector as compared to the KFS. Therefore, we dropped agricultural and mining firms from our KFS sample.

In spite of these major differences in the survey designs, we do not expect this to systematically bias the comparability of the data sets. Note that except for the variations of the survey designs there are also differences between the questionnaires. These differences will be discussed in Section 5.3.3.4.

5.3.1.4 Start-up environment in the US and in Germany

This section presents some key differences between the USA's and Germany's start-up environment to get some intuition about the environments the respective start-ups are facing.

The USA is considered to be one of the most entrepreneurial economies in the world. In contrast, the German economy still lags behind (Geibel and Manickam, 2015). For instance, there were approximately 160,000 new firms founded in Germany in every year between 2011 and 2013 (ZEW and Creditreform, 2016). In the US, about 620,000 businesses were founded between 2011 and 2013 every year.[64] Hence, there were 3.9 times more new firms founded in the US than in Germany between 2011 and 2013. This factor roughly corresponds to the difference in the labour force population between both countries and does not necessarily indicate the US to be more entrepreneurial-oriented than Germany. As we only found numbers on new establishments and not on new firms for the US, the difference of new firm foundations should be treated with caution. In principle, this means that the number of new US firms is actually less than 620,000. Hence, there are actually more firm foundations in Germany than in the US relative to the countries' labour force population.

Another way of measuring the entrepreneurial orientation of a country is conducted by the Global Entrepreneurship Monitor (GEM), an annual survey on countries' entrepreneurial activities. The GEM survey covers 73 countries and surveys at least 2,000 adults in each participating country. In addition, several experts on entrepreneurship are asked every year in each country as well. The GEM provides the total early-stage entrepreneurial activity (TEA) indicator. It is the countries' percentage of 18- to 64-year old people who founded a new firm during the past 3.5 years or are just in the process of founding a new firm. According to the 2014 Global Report, the entrepreneurial activity in Germany is very low as compared to the US. The total early-stage entrepreneurial activity (TEA) is about 5% in Germany and at about 14% in the USA (GEM, 2015). Considering the TEA, Germany performs not only poorly as compared to the US but also to almost all remaining innovation-driven economies. Furthermore, the GEM also provides information about the basic reason for starting a business. This can be opportunity-driven or necessity-driven. The former reason refers to

[64] Based on Bureau of Labor Statistics (BLS) data: http://www.bls.gov/bdm/entrepreneurship/entrepreneurship.htm.

founders who start a business because they seek to exploit growth opportunities and not because they "just" want to make a living. The latter refers to founders who saw no other option to obtain resources for living. In Germany, of the 5% TEA 76% stated to be an opportunity-driven entrepreneur, whereas the corresponding US share amounts to 82%. This means that even though there are fewer entrepreneurs in Germany than in the US, the main reason for becoming a firm founder is in principle the same.

According to Sternberg et al. (2016), who analysed specific GEM indicators for Germany only, the poor financing conditions for start-ups is one major reason that hampers the entrepreneurial activity (in Germany). As there is no information about the specific type of financing, the responding experts may have had the lack of venture capital (VC) financing in mind. VC financing actually plays an important role in financing innovative start-ups, which typically have high demand for capital (Röhl, 2014).[65] Bank lending may be an adequate alternative to venture capitalists as an external financing source but banks are more risk-averse and typically require collateral young firms do not own. Instead, venture capital firms take the risk of failure and rather see the opportunity to substantially benefit from their investments. Unfortunately, the German (and the European) VC market is poorly developed. The German VC financing amounted to about 881 million USD (0.023% of GDP) in 2014 (OECD, 2015). In contrast to Germany, the US-American venture capital market is very strong and an important financing source for start-ups. The amount invested by venture capitalists in 2014 is about 50 billion USD (0.28% of GDP) (OECD, 2015). However, these numbers have to be treated with caution as well. According to OECD (2015) data on VC is difficult to internationally compare as there is a lack of a standard international definition of VC and there are diverse methodologies employed by data compilers. Nevertheless, it is not unreasonable to assume that the US VC market is substantially larger than the German market. This implies that (promising) young US firms are more likely to get financed in order to scale their business than in Germany. In a similar line of reasoning, more risky projects are more likely to get financed in the USA than in Germany, which may lead to more radical innovations and a more robust economic development.

The second major reason hampering the start-up activity in Germany is the "foundation culture" (foundation mentality) (Sternberg et al., 2016). Like the VC market, the foundation culture in Germany is rather poorly developed. Unfortunately, it is not really possible to proof the existence or the lack of such entrepreneurial culture as it is a very fuzzy term and not strictly defined. Typically, this term refers to a society in which potential entrepreneurs are supported and motivated to start a business and where failing entrepreneurs are not stigmatised but rather encouraged to restart a new business. Whereas this culture is allegedly prevailing in the US, in Germany it's not. Some facts may give some support to this "cultural" difference. Based on the World Bank's Doing Business data base, Müller et al. (2015) find for 2014 that to start a new firm in Germany nine steps are required, whereas in the US only six steps are necessary. Further, it takes about 15 days to start a new firm in Germany as compared with the five days it takes in the USA. The average costs of starting a new firm amount to 4.8% of per capita income in Germany but only to 1.5% of per capita income in the US. Hence, the bureaucratic effort is much higher in Germany than in the US.

Even though the lack of data and precise definitions make it rather difficult to compare both start-up environments with each other, the overall conclusion does not change. The main differences in the start-up environments described in this section imply that the US environment is in principle more accessible than the German one. There are not only more new firm foundations in the US than in Germany but also a higher share of the working age

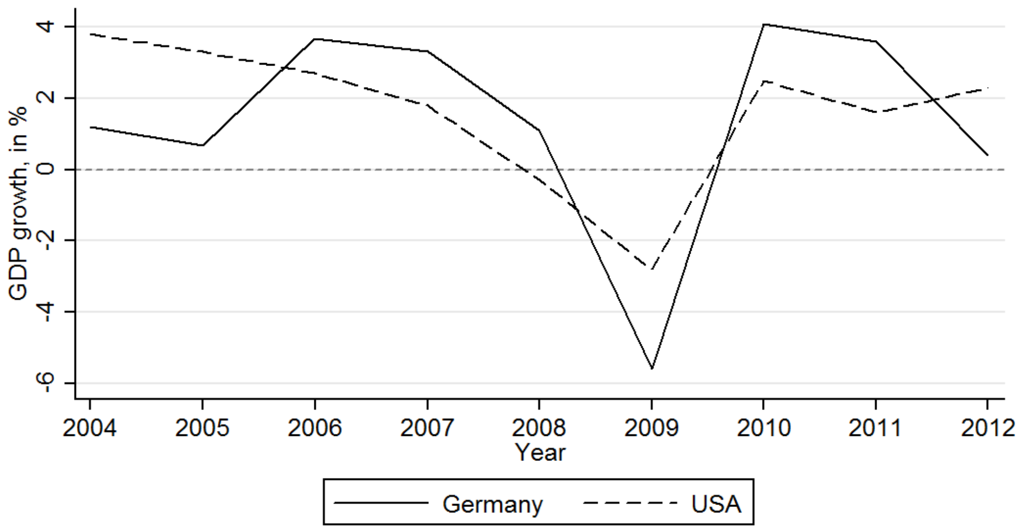
[65] For instance, Kortum and Lerner (2000) show for 20 US manufacturing industries that VC-financing has a significantly positive effect on patenting rates.

population starts new firms. Furthermore, it seems to be easier to start and to restart a new business and to get the projects financed (at least for a certain number of start-ups).

5.3.2 Business cycles

We investigate the different effects of the start-ups' R&D investment over the business cycle. In particular, we want to know whether it has been an effective strategy to increase R&D investment during the most recent recession. A comparison between the USA and Germany requires that the business cycles of the two countries have been similar over the observed periods. Figure 5.1 presents the real GDP growth rates of Germany and the USA between 2004 and 2012. In this period, both countries had a similar growth pattern. From 2004 on, the GDP growth declined until 2009, followed by a steep growth in 2010 that slowed in 2011 and 2012. However, whereas the German GDP growth made stronger leaps, the US growth was more moderate. For instance, the US GDP growth rate amounted to 3.8% in 2004 and steadily declined to 1.8% (2007) and -2.8% (2009). Even after the 2010 hike, the 2011 and 2012 GDP growth rates did not deviate by more than 0.9%-points from the 2010 growth rate (2.5%).

Figure 5.1: Real GDP growth of Germany and the USA between 2004 and 2012.



Source: World Development Indicators (World Bank); authors' own calculation.

In contrast, the German GDP growth declined between 2004 and 2005 and reached a pre-recession peak of 3.7% in 2006 before the growth rate dropped to -5.6% in 2009. Hence, the German growth rate changed by about 9.5%-points within only four years. This was anything but smooth. Furthermore, the growth rate had leaped from -5.6% (2009) to 4.1% (2010) within one year only before the GDP growth declined to 0.4% in 2012.

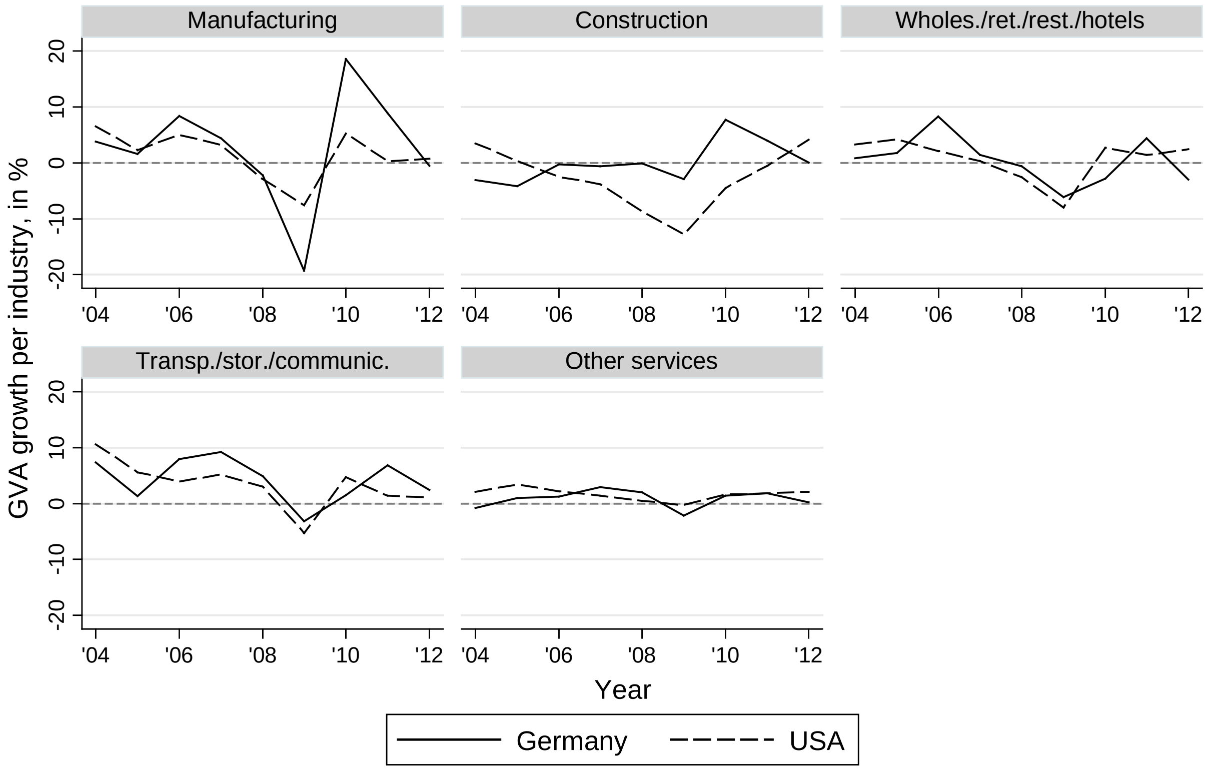
Our estimations cover the years 2007-2011 (USA) and 2007-2012 (Germany), respectively. During this period the GDP patterns were very similar with one exception. The recession period in Germany started in the second half of 2008 and ended in June 2009. In the US, the recession began in January 2008 and ended in June 2009. In our analysis, we consider 2008 and 2009 as recession years in the US and 2009 as recession year in Germany.

In general, GDP growth is only a rough business cycle indicator from a firm perspective as it only represents an average annual value across all markets. It does not account for heterogeneous industry-specific impacts of shocks. For instance, many industries may have been severely affected by the most recent recession. However, some industries may have not significantly suffered from the macroeconomic drop. Therefore, a potentially more accurate economic indicator refers to the firms' focal industry.

Figure 5.2 presents the developments of the annual real gross value added (GVA) growth on an aggregated industry level (ISIC 3.1) for Germany and the US. This is the only indicator we have found that fulfils the following criteria: (i) it is available for the observed periods for the US and Germany, (ii) it is measured in comparable real terms, (iii) it is a comparable macroeconomic indicator and (iv) it is available on an industry-level. Figure 5.2 shows the graphs of manufacturing, construction, wholesale/retail/restaurants/hotels (Wholes./ret./rest./hotels), transport/storage/communication (Transp./stor./communic.) and of other services over the period of 2004 to 2012.

The graphs of the manufacturing sector largely reproduce the pattern of the countries' GDP growth during the period. From 2006 on GVA growth declined until 2009, peaked in 2010 and decreased until 2012. The GVA growth of the German manufacturing sector declined much stronger (-19.3%) than the US manufacturing sector (-7.6%) in 2009, whereas the peak in 2010 was more pronounced in Germany (18.6%) than in the US (5.3%). The graphs of the construction sector indicate a dissimilar development. The US construction industry's GVA growth continuously decreased from 3.5% (2004) to -12.8% (2009) and started to recover after 2009. This development is most likely related to the burst of the US-American housing price bubble in 2007, which led to an economic crisis until the middle of 2009 that was followed by an economic recovery. The German construction market does not seem to have been severely affected (-2.9% in 2009) and could even considerably benefit (7.7%) from the economic boom in 2010. The growth patterns for the remaining three sectors are similar between the US and Germany. In particular, the sector "other services" did not experience substantial cyclical fluctuations but rather shows a very smooth pattern for both countries during 2004-2012.

Figure 5.2: Industry-level annual real GVA growth of Germany and the USA between 2004 and 2012.



Source: Country- and industry-specific gross value added (GVA) growth on an aggregated ISIC 3.1 level from the UN data base; authors' own calculation.

5.3.3 Variables[66]

5.3.3.1 Dependent variable

We choose an employment growth indicator as our measure of new firm growth. We define our dependent variable, *ln_empgr*, as first-difference of the log of the number of full-time equivalents. A common way to measure new firm growth is to take the sales growth or the employment growth (Gilbert et al., 2006). In principle, sales growth measures the product/service acceptance of the firms' customers. The advantage of taking sales growth is that a firm can have or increase its sales growth without recruiting more staff. For instance, a firm may become more productive and even reduces its employment level. However, we use employment growth as a sales-based indicator does not take some of the new firms' peculiarities properly into account. In particular, more research-intensive new firms may take their time to market a product. If a firm did not have sales, which happens among new firms, it would not have any sales growth. Coad et al. (2013b) find that new firms put more emphasis on employment growth than old firms. Accordingly, by hiring new employees the firms invest in one of their key assets, i.e. human resources. In this sense, they build up absorptive capacity that improves the new firms' ability to assess the external environment, which is an important prerequisite for start ups' sustainability.

5.3.3.2 Independent variables

To analyse the employment growth effects of R&D investment, we use the firms' R&D intensity. We define the intensity as firm-level R&D expenditures divided by the number of full-time equivalents and refer to it as *rnd*. In addition, we want to investigate whether or not an increase in firms' R&D investment can induce employment growth. For this reason, we use the annual difference of the firms' R&D intensity, *rnd_diff*. To control for potential business cycle effects, we interact *rnd* and *rnd_diff* with the country-specific annual real GDP growth rates (*gdpgr*) and the country- and industry-specific annual real GVA growth rates (*gvaindgr*), respectively. These interaction terms are labelled as *rnd_gdpgr* (*rnd_diff_gdpgr*) and *rnd_gvaindgr* (*rnd_diff_gvaindgr*), respectively.

5.3.3.3 Control variables

In line with prior research, we differentiate the control variables into entrepreneurial characteristics and firm characteristics (see e.g. Gilbert et al., 2006; Wright and Stigliani, 2012; Gottschalk et al., 2014). A new firm is considered to be an extension of the founders (Gilbert et al., 2006). Therefore, their educational background, skills and experience are key determinants for post-entry success. We use three different indicators to measure the founders' human capital: (i) a dummy indicating whether at least one the founders has started a business in the past or not, *founded_before*, (ii) the log of the years of the founders' industry experience, *ln_experience*, and (iii) a dummy indicating whether or not at least one of the founders has obtained at least a bachelor degree, *degree*.[67] Furthermore, we control for the gender of the founders by a dummy variable, *female*. It takes on the value one if at least one woman has been part of the founding team. Firm characteristics we control for include the log of the firms' age (*ln_age*), whether the firms' active owners have been organised as a team or not (*team*) and a dummy variable indicating whether the firm has been located in a metropolitan area or not (*metro*). In addition, to control for potential financial constraints, we use the firms' credit rating and construct the dummy variable *delinq*. It indicates the firms' likelihood of becoming severely delinquent in its payments over the next 12-month period. If

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[66] A list of the variables' definitions that also includes an indicator for country differences is presented in Table 5.A.1 in the Appendix.

[67] Note that the information on *ln_experience* is based on the founder with the highest industry experience.

the likelihood was at least 14%, which refers to a weak or worse credit rating, the dummy would take on the value one. In this case, the incidence of delinquency becomes very likely. Further, we include a dummy variable measuring whether the firm has used any debt financing options or not, *debt*.

Harhoff et al. (1998) find that the liability issue is an important determinant for firm growth. Therefore, we include dummies to measure the firms' legal status, i.e. whether the firm has been a sole proprietorship (*sole*), partnership (*partner*), corporation (*corp*) or limited liability company (*llc*). In contrast to *corp* and *llc*, *sole* and *partner* refer to legal forms in which the owners have to take full liability. In addition, we control for the firms' capability to grow by using the first-difference of the log of the capital stock, *ln_capstockgr*, Furthermore, we include the log of the number of full-time employees, *ln_emp*, and a dummy that indicates whether a firm has a comparative advantage or not, *compad*. We also include a set of industry dummies. Due to strong collinearity with GDP growth, which is largely owed to the rather short time period, we do not include time dummies in our estimations. However, our results would not substantially change if time dummies were included and GDP growth was excluded.

5.3.3.4 Differences between KFS and SUP variables

The questionnaires of both surveys are quite similar. Nevertheless, there are some notable differences between the questionnaires' phrasing of specific questions that may be relevant to our control variables. The first difference relates to *ln_capstockgr*. The SUP asked about the amount of the annual firm investment in tangible assets. This means, the capital stock in year t is calculated as a depreciated sum of all previous investments that have been made until year t-1 plus the (non-depreciated) amount of investment in year t. We set the depreciation rate to 10%. Instead, the KFS annually asked about the value of different types of tangible assets. Hence, to calculate the capital stock for the US sample we did not need to use a depreciation rate. We just added up the different types of tangible investments every year. The second difference is linked to *debt*. The KFS specifically asked about two separate things: (i) whether or not the owners have used given types of external debt financing in their names on behalf of the firm and (ii) whether or not the given types of debt financing may have been obtained in the name of the business. To construct the dummy variable *debt* for the US sample, we used both information because (i) and (ii) eventually refer to the firms' leverage. The SUP only asked about the types of debt financing the firm has used (on behalf of the firm).

Third, the likelihood of delinquency is differently measured. The German credit rating indicator is a continuous variable, distributed between 100 and 600. Based on this, the dummy variable *delinq* would take on the value one if the individual credit rating was larger than 350, which refers to a likelihood of severe delinquency of at least 14%. In the German case, a likelihood of at least 14% refers to a firm that has a weak or worse credit rating. The US credit rating indicator is an interval variable that has only five different values. Each value, i.e. each "credit score risk class", refers to a specific credit score interval, which has a particular likelihood of severe delinquency assigned to it. The US dummy would take on the value one if the likelihood of severe delinquency was at least 14%. The difference between the German and the US indicator is not the definition itself but rather the number of firms. In the German sample only a few hundreds of observations have a likelihood of severe delinquency of at least 14%. In the US sample, more than half of the observations have such a high likelihood (see Table 5.1). We think that this difference may be due to different information (or weights) having been used by the agencies to calculate these likelihoods.

Fourth, whereas the KFS asked about the information on a firm's comparative advantage every year, the SUP only asked for this information in 2008. Fifth, we could easily assign the US-American legal forms to the dummies *sole*, *partner*, *corp* and *llc*. It was a bit more complicated in the German case. Germany has more legal forms than the USA. We used the classifications of Harhoff et al. (1998) and considered three types of sole proprietorships as sole proprietorship ("Einzelunternehmen", "Gewerbebetriebe", "Freiberufler"). Furthermore, partnerships pool the civil law association ("Gesellschaft bürgerlichen Rechts"), the limited commercial partnership ("Kommanditgesellschaft") and the general commercial partnership ("Offene Handelsgesllschaft"). In the last group, *llc*, we include the limited liability firms ("Gesellschaft mit beschränkter Haftung"), the limited commercial partnerships formed with a limited liability firm (GmbH & Co. KG) and the stock-based corporate firms ("Aktiengesellschaft").[68]

Sixth, the metropolitan statistical areas of the USA are subject to a specific official definition (see OMB, 2010). In contrast, there is no official precise definition of a metropolitan area in Germany, (see IKM, 2007). Nevertheless, the metropolitan areas according to IKM (2007) cover the economically most important and most densely populated areas in Germany. Seventh, the SUP sample includes two variables not included in the KFS. To control for the structural differences between Eastern German and Western German states, we include a dummy variable indicating whether the firm has been located in Eastern Germany or not, *east*. In addition, one of the SUP sampling criteria was whether a firm has been financially supported by the KfW or not, *kfw*. This dummy is included in the sample and estimations but its values cannot be displayed due to reasons of confidentiality. Eighth, the KFS includes a variable indicating whether or not the survey has been completed via telephone, *cati*. Ninth, the SUP covers ten different sectors, which we aggregated to nine. That is, high-tech manufacturing, non-high-tech manufacturing, technology-intensive industries, software supply and consultancy, skill-intensive services, other business-oriented services, consumer-oriented services, construction and wholesale/retail. These industry classifications were constructed based on the European NACE Rev. 2. In contrast, the KFS industry information is based on the North-American NAICS 2007. To bring the nine SUP industry dummies in line with the KFS industry classification, we used NACE-NAICS correspondence tables offered by the European statistical office (Eurostat).[69] However, not all of the NAICS codes could be converted into a comparable NACE code. Therefore, our KFS estimations include another industry dummy covering the NAICS codes that could not be converted into NACE codes and the nine industry dummies, respectively. Tenth, the monetary variables are measured in thousands of local currency units, i.e. USD and EUR, respectively. Furthermore, we deflated these variables by the respective country-specific GDP deflators, provided by the World Bank data base.

5.3.3.5 Descriptive statistics

Table 5.1 presents the descriptive statistics of the variables we use in the estimations of the R&D intensity level, *rnd*, and the related interaction terms.[70] On average, the German start-ups' employment level has grown stronger than the corresponding US-American level over the period of 2007-2012 and 2007-2011, respectively. In terms of R&D investment, the US start-ups had an average level of 870 USD per full-time equivalent. This value is approximately the half of the German value of 1,680 EUR per full-time equivalent. Hence, the average German start-up has invested more in R&D activities relative to its size than the average US- American start-up.

[68] Stock-based corporate firms should be actually included in *corp*. However, our main SUP sample only includes four stock-based observations. Corporate firms also have limited liability, so we included them in *llc*.

[69] You can find the correspondence tables here: http://ec.europa.eu/eurostat/ramon/miscellaneous/index.cfm?TargetUrl=DSP_NACE_2_US_NAICS_2007.

[70] Tables on the descriptive statistics of the manufacturing firms and the annual difference of the R&D intensity are presented in Table 5.A.2 and Table 5.A.3, respectively.

Table 5.1: Descriptive statistics of the regressions of employment growth on the level of the R&D intensity

Variables	**Germany**				**USA**	
Dependent var.:	Mean	Std. dev.	Min	Max	Mean	Std. dev.
ln_empgr	0.03	0.39	-2.08	2.08	-0.02	0.40
Independent vars.:						
rnd	1.68	5.82	0	51.4	0.87	3.83
gdpgr	1.54	3.23	-5.6	4.10	0.32	2.01
gdpgr_at_t	0.22	3.51	-5.6	4.10	0.12	2.02
rnd_gdpgr	2.53	21.65	-288	194	0.23	7.99
gvaindgr	1.20	5.46	-19.3	18.6	-0.35	3.63
gvaindgr_at_t	0.09	5.96	-19.3	18.6	-0.50	3.64
rnd_gvaindgr	2.60	30.79	-576	449	-0.16	15.60
Controls:						
Firm vars.:						
ln_emp	0.97	0.85	0	4.62	0.88	0.94
ln_capstockgr	0.14	0.48	-0.11	11.71	-0.01	3.65
capstockmiss	0.01	0.08	0	1	0.27	0.44
ln_age	1.66	0.25	1.39	2.08	1.84	0.18
debt	0.23	0.42	0	1	0.76	0.43
delinq	0.05	0.21	0	1	0.56	0.50
delinqmiss	0.03	0.16	0	1	0.13	0.34
compad	0.91	0.28	0	1	0.49	0.50
sole	0.64	0.48	0	1	0.31	0.46
partner	0.10	0.31	0	1	0.03	0.17
corp					0.32	0.47
llc	0.26	0.44	0	1	0.33	0.47
team	0.23	0.42	0	1	0.29	0.46
metro	0.65	0.48	0	1	0.82	0.38
east	0.18	0.39	0	1		
cati					0.23	0.42
Founder vars.:						
ln_experience	2.74	0.58	1.39	3.93	2.84	0.62
founded_before	0.33	0.47	0	1	0.47	0.50
degree	0.42	0.49	0	1	0.60	0.49
female	0.14	0.35	0	1	0.34	0.47
Industries:						
High-tech manufacturing	0.08	0.27	0	1	0.06	0.24
Non-high-tech manufacturing	0.12	0.32	0	1	0.08	0.27
Technical services	0.24	0.43	0	1	0.09	0.29
Software	0.09	0.28	0	1	0.02	0.14
Knowledge-intensive services	0.07	0.26	0	1	0.08	0.27
Consumer-oriented services	0.13	0.34	0	1	0.22	0.41
Other services	0.04	0.19	0	1	0.19	0.40
Construction	0.12	0.32	0	1	0.08	0.27
Wholesale/retail	0.12	0.32	0	1	0.16	0.37

Source: KfW/ZEW Start-Up Panel (Germany) and Kauffman Firm Survey (USA); authors' own calculation.
Note: The number of observations for the German sample is 2,386 and for the US sample 7,291; due to confidentiality reasons we are not allowed to present the min and max values for the US sample; we are also not allowed to present the values of the kfw dummy variable.

This also becomes apparent in case the R&D intensity is interacted with business cycle information. The mean value of *rnd_gdpgr* is 2.53 in the German sample, whereas it is only 0.23 in the American sample. A similar discrepancy appears in the case the R&D intensity is interacted with the industry-specific GVA growth. In this case, the value is even negative in the US sample. With respect to the control variables, the US start-ups have used external debt financing options much more often than the German start-ups. Furthermore, about 90% of the German firms stated to have a comparative advantage, whereas only 49% of the US firms have had a comparative advantage. There are also much more sole proprietorships in the German sample (64%) than in the US sample (31%). However, this does not mean that there have been more single-owned start-ups in Germany than in the US. In fact, both samples include about the same share of single-owned businesses, 77% in Germany and 71% in the US (see *team* in Table 5.1). Regarding the founder characteristics, the German and the American samples are quite similar. A notable difference refers to the share of female founders. In the US, about 34% of the firms include at least one female founder, whereas in the German sample it is only 14%. As mentioned in Section 5.3.1.1, being a woman was one sample criterion in the KFS. In the SUP, gender was not a criterion, which may have caused an undersampling of female-owned start-ups.

According to Table 5.1, the samples' industry distributions largely coincide, even though there are three major differences. First, 24% of the German observations are associated with technical services, whereas only 9% of the KFS observations refer to technical services. Second, there are much more consumer-oriented service firms in the US sample (22%) than in the German sample (13%). Third, 19% of the US observations refer to other services firms, whereas the corresponding share in the SUP sample is only 4%. These differences may indicate that some German start-ups have a completely different focus or that the conversion from NAICS to NACE has not been overly accurate to some extent. These are two more reasons for us to perform additional split sample regressions for the manufacturing start-ups.

5.4 Empirical method and results

5.4.1 Estimation models

Our dependent variable, the log difference of the number of full-time equivalents, is continuously distributed. For this reason, we rely on OLS estimations. We estimate two different models for firm i of country j. The first model estimates a basic specification including R&D intensity:

$$(5.1) \qquad ln\_empgr_{ij,t|t-1} = \beta_0 + \beta_1 rnd_{ij,t-1} + \beta_2 gdpgr_{j,t|t-1} + \beta_3 X_{ij,t} + \beta_4 Z_{ij,t-1} + u_{ij,t}$$

The second model controls for business cycle effects of R&D investment by using an interaction term between R&D intensity and the annual GDP growth:

$$(5.2) \quad ln\_empgr_{ij,t|t-1} = \beta_0 + \beta_1 rnd_{ij,t-1} + \beta_2 rnd_{ij,t-1} * gdpgr_{j,t-1|t-2} + \beta_3 gdpgr_{j,t-1|t-2} + \beta_4 gdpgr_{j,t|t-1} + \beta_5 X_{ij,t} + \beta_6 Z_{ij,t-1} + u_{ij,t}$$

We estimate the equations (5.1) and (5.2) not only by using GDP growth indicators but also by using the industry-specific GVA growth indicators that we have constructed equivalently (see Section 5.3.3.2). In addition, both models are estimated with $rnd\_diff_{ij,t-1|t-2}$ and the respective interaction terms instead of $rnd_{ij,t-1}$ and its interaction terms. The vector $Z_{ij,t-1}$ includes the control variables observed at t-1, i.e., *ln_emp*, *ln_capstockgr*, *capstockmiss*, *debt*, *delinq* and *delinqmiss*. The other control variables are measured at t and are included in the vector $X_{ij,t}$. The entrepreneurial characteristics are also included in $X_{ij,t}$, even though *founded_before*, *degree* and *female* are not available at t in both surveys but only at the founding year.

5.4.2 Estimation results of the level of R&D intensity

Table 5.2 presents the employment growth effects of the R&D intensity level for the German and the US-American start-ups. Model I shows the very basic results of R&D and employment growth. In Germany, an increase of the R&D intensity by one unit, i.e. 1,000 EUR per full-time equivalent, approximately leads to a 0.4 percentage points higher employment growth. This means that if a German start-up increased its R&D-to-labour ratio by ten units (= 10,000 EUR per full-time equivalent) it would have a 4 percentage points (pp) higher employment growth than other start-ups, on average. With respect to the US sample, the employment growth effect of R&D is 0.2 pp in the case of a one unit increase of the R&D indicator. Indeed, it is not significant but it implies a growth-inducing effect triggered by R&D investment among the US start-ups. In contrast to the German sample, employment growth in the US is significantly driven by GDP growth (at year t). Model II includes an interaction term measured at t-1 between the R&D intensity and the country-specific GDP growth. The estimated interaction effect is weak in magnitude and insignificant in the German as well as in the US sample. The German interaction effect implies counter-cyclicality, which indicates that a higher R&D investment level during recessions would lead to higher subsequent employment growth among start-ups. However, model II does not disclose a counter-cyclical effect in the US sample. Model III estimates the interaction effect between the R&D intensity and country- and industry-specific GVA growth. The R&D estimates do not change in the German sample and even the indication of a counter-cyclical effect remains. In contrast to the model II results, a counter-cyclical effect appears in the US sample. This implies that a potential counter-cyclicality may depend on the underlying industry.

The control variables' estimates largely coincide between the German and the US start-ups. This implies that our samples are not structurally different from each other. One difference is that the estimated coefficients of the US sample are more often significant. This may be due to the larger sample size. Another difference is that the sole proprietorships (*sole*) and limited liability companies (*llc*) grow significantly faster than the partnerships (reference category) in Germany as compared to the US. With respect to the entrepreneurial characteristics, the main difference is the estimate of the female dummy. Having at least one woman in the founder team does not significantly affect the employment growth of German start-ups. In contrast, female-founded businesses have a significantly lower employment growth among the US than among the German start-ups. Hence, there seems to be a gender gap in the US. There could also be one in Germany that may not appear due to potentially undersampled female-founded start-ups.

The results of the models I-III indicate a job-creating effect of R&D investment for both countries' start-ups. In addition, this job-creating effect tends to be even stronger during recession periods. Hence, for start-ups it may be desirable to seek new growth opportunities during the recovery period by investing more in R&D during economic slumps.

Table 5.2: Employment growth effects of R&D intensity over the business cycle

	Germany			USA		
Dep. var.: ln_empgr	I	II	III	I	II	III
rnd	**0.004****	**0.004****	**0.004*****	0.002	0.002	0.002
	(0.001)	(0.002)	(0.002)	(0.001)	(0.001)	(0.001)
rnd_gdpgr		-0.000			0.000	
		(0.000)			(0.001)	
gdpgr		-0.003			0.003	
		(0.003)			(0.002)	
gdpgr_at_t	0.003	0.003		**0.008****	**0.008****	
	(0.002)	(0.002)		(0.003)	(0.003)	
rnd_gvaindgr			-0.000			-0.000
			(0.000)			(0.000)
gvaindgr			-0.002			0.002
			(0.002)			(0.002)
gvaindgr_at_t			0.002			**0.006*****
			(0.002)			(0.002)
Controls:						
ln_emp	**-0.125*****	**-0.125*****	**-0.125*****	**-0.139*****	**-0.139*****	**-0.139*****
	(0.015)	(0.015)	(0.015)	(0.009)	(0.009)	(0.009)
ln_capstockgr	**0.043***	**0.043***	**0.044***	0.002	0.002	0.002
	(0.023)	(0.023)	(0.023)	(0.001)	(0.001)	(0.001)
capstockmiss	-0.091	-0.091	-0.092	**-0.029*****	**-0.029*****	**-0.029*****
	(0.212)	(0.213)	(0.213)	(0.010)	(0.010)	(0.010)
ln_age	0.023	0.018	0.024	0.040	0.042	**0.046***
	(0.032)	(0.031)	(0.031)	(0.032)	(0.032)	(0.028)
debt	0.016	0.016	0.016	0.017	0.017	**0.018***
	(0.019)	(0.019)	(0.019)	(0.011)	(0.011)	(0.011)
delinq	-0.019	-0.021	-0.019	**-0.020****	**-0.020****	**-0.021****
	(0.043)	(0.044)	(0.043)	(0.010)	(0.010)	(0.010)
delinqmiss	-0.057	-0.055	-0.056	**-0.039*****	**-0.039*****	**-0.039*****
	(0.048)	(0.048)	(0.048)	(0.014)	(0.014)	(0.014)
compad	0.019	0.019	0.018	**0.046*****	**0.045*****	**0.046*****
	(0.023)	(0.023)	(0.023)	(0.009)	(0.009)	(0.009)
sole	**0.086****	**0.086****	**0.087****	-0.011	-0.012	-0.011
	(0.035)	(0.035)	(0.035)	(0.023)	(0.024)	(0.024)
corp				0.036	0.036	0.035
				(0.023)	(0.023)	(0.023)
llc	**0.129*****	**0.129*****	**0.129*****	0.009	0.008	0.009
	(0.032)	(0.032)	(0.032)	(0.023)	(0.023)	(0.023)
team	**0.190*****	**0.189*****	**0.191*****	**0.158*****	**0.158*****	**0.158*****
	(0.031)	(0.031)	(0.031)	(0.014)	(0.014)	(0.014)
metro	0.023	0.023	0.023	**0.022****	**0.022****	**0.022****
	(0.017)	(0.017)	(0.017)	(0.010)	(0.010)	(0.010)
east	-0.023	-0.023	-0.023			
	(0.019)	(0.019)	(0.019)			
cati				**0.030*****	**0.030*****	**0.030*****
				(0.011)	(0.011)	(0.011)
ln_experience	-0.014	-0.014	-0.015	0.002	0.002	0.002
	(0.015)	(0.015)	(0.015)	(0.006)	(0.006)	(0.006)
founded_before	-0.005	-0.005	-0.005	0.002	0.002	0.002
	(0.019)	(0.019)	(0.019)	(0.008)	(0.008)	(0.008)
degree	-0.005	-0.005	-0.004	-0.007	-0.007	-0.006
	(0.017)	(0.017)	(0.017)	(0.009)	(0.009)	(0.009)
female	0.000	0.000	-0.000	**-0.038*****	**-0.038*****	**-0.037*****
	(0.022)	(0.022)	(0.022)	(0.009)	(0.009)	(0.009)
Constant	0.036	0.050	0.045	-0.016	-0.020	-0.015
	(0.076)	(0.076)	(0.075)	(0.071)	(0.071)	(0.066)
Observations	2,386	2,386	2,386	7,291	7,291	7,291
R2_adjusted	0.063	0.063	0.064	0.075	0.075	0.075
Industry dummies (F):	**2.580****	**2.610****	**2.820*****	**2.820*****	**2.820*****	**3.550*****

Source: SUP (Germany) and KFS (USA); authors' own calculation.
Note: *** p<0.01, ** p<0.05, * p<0.1; standard errors – in parentheses – are clustered at the firm level.

5.4.3 Estimation results of the annual difference of R&D intensity

Table 5.3 presents the results in case the business cycle indicators are interacted with the annual difference of the R&D intensity. This allows us to estimate the job-creating effect of a direct increase of R&D investment over the business cycle. The estimates of *rnd_diff* are positive but insignificant across the models of both countries. Hence, increasing R&D investment tends to be related to higher start-up employment growth. This basic finding holds for both countries and largely corresponds to the findings of Table 5.2. In this respect, a counter-cyclical effect of increasing R&D investment appears in the German sample only when the interaction term is measured by GVA growth and not by GDP growth. Regarding the KFS sample, the negative estimates of both interaction terms indicate a counter-cyclical employment effect of increased R&D investment.

Table 5.3: Employment growth effects of the difference of R&D intensity over the business cycle

	Germany			USA		
Dep. var.: ln_empgr	IV	V	VI	IV	V	VI
rnd_diff	0.003	0.003	0.003	0.001	0.001	0.001
	(0.003)	(0.003)	(0.004)	(0.003)	(0.003)	(0.003)
rnd_diff_gdpgr		0.000			-0.001	
		(0.001)			(0.001)	
gdpgr		-0.005			0.004	
		(0.005)			(0.003)	
gdpgr_at_t	**0.006***	0.002		0.005	**0.010*****	
	(0.003)	(0.004)		(0.004)	(0.002)	
rnd_diff_gvaindgr			-0.000			-0.000
			(0.000)			(0.001)
gvaindgr			-0.002			0.000
			(0.002)			(0.002)
gvaindgr_at_t			0.002			**0.006****
			(0.002)			(0.002)
Constant	0.230	0.051	0.070	-0.122	**0.082***	-0.074
	(0.146)	(0.212)	(0.135)	(0.160)	(0.045)	(0.151)
Observations	1,388	1,388	1,388	5,106	5,106	5,106
R2_adjusted	0.072	0.072	0.070	0.067	0.067	0.068
Industry dummies (F):	1.610	1.610	1.580	**2.010****	**2.010****	**2.220****

Source: SUP (Germany) and KFS (USA); authors' own calculation.

Note: *** p<0.01, ** p<0.05, * p<0.1; standard errors – in parentheses – are clustered at the firm level; the full table is presented in the Appendix (see Table 5.A.4).

5.4.4 Estimation results for the subset of manufacturing firms

The results of Table 5.2 and of Table 5.3 largely imply that higher R&D investment during recessions can be an effective way for German and US start-ups to induce employment growth. However, our estimates may not be accurate enough due to the difference in the industry distributions and due to the fact that manufacturing firms are the most important R&D performers. According to Table 5.1, service firms make the largest share in both samples and these may not be overly intensive R&D performers. For these reasons, this section focusses on manufacturing firms only.

Table 5.4 presents the estimates of the R&D intensity level for manufacturing firms. The estimated coefficients for the SUP sample are stronger than the ones estimated for the sample including all sectors presented in Table 5.2. For instance, a 10 unit increase of the level of

R&D intensity is related to a higher employment growth of 7 pp and 9 pp, respectively. We even find a significant counter-cyclical employment growth effect of R&D investment. Given negative GDP growth, an increase of the R&D intensity by ten units would induce an additional employment growth of 2 pp. A counter-cyclical effect can also be found in case the interaction term is based on GVA growth, even though this effect is not significant. In contrast, no significant employment effect of R&D appears in the KFS sample. In addition, there is no indication of a counter-cyclical employment effect but rather a pro-cyclical effect in the US sample.

Table 5.4: Employment growth effects of the level of R&D intensity for manufacturing firms

	Germany			**USA**		
Dep. var.: ln_empgr	VII	VIII	IX	VII	VIII	IX
rnd	**0.007****	**0.009*****	**0.007****	0.003	0.002	0.003
	(0.003)	(0.003)	(0.003)	(0.002)	(0.002)	(0.002)
rnd_gdpgr		**-0.002*****			0.002	
		(0.001)			(0.001)	
gdpgr		-0.006			-0.005	
		(0.006)			(0.007)	
gdpgr_at_t	0.008	0.006		**0.027*****	**0.027*****	
	(0.007)	(0.007)		(0.008)	(0.008)	
rnd_gvaindgr			-0.000			0.001
			(0.000)			(0.000)
gvaindgr			-0.002			0.000
			(0.002)			(0.003)
gvaindgr_at_t			0.002			**0.012*****
			(0.002)			(0.004)
Constant	0.046	0.121	0.068	-0.160	-0.159	-0.172
	(0.174)	(0.166)	(0.186)	(0.175)	(0.176)	(0.174)
Observations	471	471	471	952	952	952
R2_adjusted	0.089	0.107	0.097	0.039	0.040	0.041
Industry dummies (F):	0.290	0.460	0.400	0.050	0.040	0.040

Source: SUP (Germany) and KFS (USA); authors' own calculation.

Note: *** p<0.01, ** p<0.05, * p<0.1; standard errors – in parentheses – are clustered at the firm level; the full table is presented in the Appendix (see Table 5.A.5).

Table 5.5 presents the estimated coefficients of the annual difference of the R&D intensity for manufacturing firms. In the German manufacturing sample, a direct increase of the R&D intensity is weakly negatively related to employment growth, though not significant. This may be a bit puzzling as we expect more R&D investment to induce higher employment growth and not the other way around. This (insignificant) negative effect is in contrast to the positive significant effects we have found for the level of R&D intensity earlier. The level of the R&D intensity rather refers to an industry perspective. In this sense, a general higher level of R&D investment may be more industry-induced as compared to a direct increase of the investment amount, which is more a firm-level approach. Hence, we find for the German manufacturing start-ups that a higher level of R&D intensity is associated with higher employment growth particularly during recession periods. However, a direct increase of the R&D intensity, which may strongly deviate from an industry-average, rather seems to be counterproductive.

In contrast to the German sample, the US manufacturing start-ups show a positive employment effect of a direct increase of the R&D intensity, which is also higher than for the R&D intensity level (see Table 5.4). This indicates that the industry-perspective may be less relevant for the US start-ups to create jobs by investing in R&D. Instead, firms rather induce employment growth by directly investing more resources in R&D investment. In particular, this has been effective during the recession of 2008/2009. Those US manufacturing start-ups that increased their R&D intensity between 2008 and 2009 could gain from higher employment growth in the following upswing year of 2010. That is, if a manufacturing start-up increased its R&D investment by 1,000 USD (at a constant employment level) in 2009 as compared to 2008, it could gain from 0.5 pp higher employment growth in 2010. The effect alleviates to 0.2 pp in case the industry-specific GVA growth was negative.

Table 5.5: Employment growth effects of the difference of R&D intensity for manufacturing firms

	Germany			**USA**		
Dep. var.: ln_empgr	X	XI	XII	X	XI	XII
rnd_diff	-0.003	-0.003	-0.004	0.007	0.006	0.004
	(0.004)	(0.004)	(0.005)	(0.005)	(0.004)	(0.004)
rnd_diff_gdpgr		0.000			**-0.005****	
		(0.002)			(0.002)	
gdpgr		-0.007			-0.004	
		(0.011)			(0.007)	
gdpgr_at_t	0.011	0.005		**0.031*****	**0.028*****	
	(0.008)	(0.012)		(0.011)	(0.007)	
rnd_diff_gvaindgr			-0.000			**-0.002****
			(0.000)			(0.001)
gvaindgr			-0.002			-0.029
			(0.003)			(0.030)
gvaindgr_at_t			0.001			-0.019
			(0.003)			(0.032)
Constant	0.471	0.227	0.149	0.065	-0.028	-3.382
	(0.333)	(0.481)	(0.445)	(0.441)	(0.113)	(3.403)
Observations	266	266	266	657	657	657
R2_adjusted	0.103	0.097	0.100	0.037	0.046	0.044
Industry dummies (F):	**3.710***	**3.710***	**3.570***	0.190	0.080	0.060

Source: SUP (Germany) and KFS (USA); authors' own calculation.

Note: *** p<0.01, ** p<0.05, * p<0.1; standard errors – in parentheses – are clustered at the firm level; the full table is presented in the Appendix (see Table 5.A.6).

As our R&D indicators denote a ratio or an annual difference thereof, one obvious concern is that the start-ups observed during the recent recession cut their employment level, which would have increased their R&D intensity by construction. In fact, this is not the case in our samples. The average amount of R&D spent during 2009 (9,400 EUR) increased as compared to the 8,300 EUR of 2008. In addition, the level of full-time equivalents stayed the same, at about 4 in 2009 as well as in 2008.[71]

Our findings present first evidence as to positive employment growth effects of a counter-cyclical R&D investment by start-ups. In principle, new firms tend to be more sensitive to business cycle fluctuations (see e.g. Fort et al., 2013; Lee and Mukoyama, 2015) than old firms. Our results suggest that new firms are not generally doomed during recession periods. According to Davidsson et al. (2010), new firms are expected to be in a better position to take advantage of growth opportunities compared to established firms. Hence, stronger R&D investment may have helped the firms to identify and exploit such growth opportunities in the upswing year 2010. For instance, if new firms combined higher R&D investment with product differentiation it would allow them to find and exploit market niches (Dowling and McGee, 1994; Del Monte and Papagni, 2003). Start-ups are more dependent on their ability to

[71] Note that similar values appear in the KFS sample.

fully utilise their resources (Kreiser, 2011). This indicates that during a recession, i.e. when the opportunity costs of R&D in terms of forgone output is low, those start-ups that shifted idle production resources to R&D activities were more able to fully utilise their resources. As a result, they may had higher employment growth in 2010. This shift of resources may be particularly conceivable for new firms. For them it could be easier to employ a "production worker", as for instance on product development issues, for some time compared to established firms where the administrative effort may be more crucial. These considerations may explain why we find counter-cyclical employment growth effects of R&D investment.

5.4.5 Survivorship bias

One problem analyses about new firm growth may suffer from is a survivorship bias (Garnsey et al., 2006). We can only estimate effects for firms that have survived until year t, thus our estimates can be biased upwards. In this sense, it could be that more R&D-intensive firms are more likely to exit than other firms. This section presents some investigations concerning a potential survivorship bias.

Table 5.6: Descriptive statistics (t-tests) for German start-ups, restricted to the years 2005-2007

Germany	Observed only the first 3 years N = 916		Observed the whole period N = 833		
	Mean	Std.dev.	Mean	Std.dev.	p-value
Dependent var.:					
ln_empgr	0.12	0.35	0.13	0.32	0.32
Firm vars.:					
ln_emp	0.67	0.81	0.76	0.69	0.01
ln_age	0.91	0.20	0.90	0.20	0.57
delinq	0.02	0.14	0.01	0.11	0.27
compad	0.88	0.32	0.92	0.27	0.01
sole	0.71	0.45	0.59	0.49	0.00
partner	0.08	0.27	0.12	0.33	0.00
llc	0.21	0.41	0.29	0.46	0.00
team	0.19	0.40	0.29	0.45	0.00
metro	0.64	0.48	0.65	0.48	0.70
east	0.17	0.37	0.17	0.37	0.99
Founder vars.:					
ln_experience	2.36	0.75	2.52	0.74	0.00
founded_before	0.33	0.47	0.33	0.47	0.91
degree	0.32	0.47	0.46	0.50	0.00
female	0.19	0.39	0.16	0.36	0.05

Source: SUP; authors' own calculation.

Table 5.6 shows basic descriptive statistics between observations that could only be observed during the first three years after foundation, i.e. during 2005-2007, and firms that could be observed during the whole 8-year period.[72] We restricted the statistics of the 8-year survivors to the years 2005-2007 as well to be able to compare the characteristics with the firms that could be observed for the first three years only. Note that not all variables we used in our estimations are available for the period 2005-2007, as for instance R&D expenditures. Therefore, we only focussed on those variables that are available. This table indicates large

[72] Whereas the former type of observations include those firms that exited and those firms that dropped out due to non-response (but may be still alive), the firms observed over 8-years, however, have survived and responded over the whole period.

differences between both types of observations in terms of the legal forms and two of the founder characteristics. For instance, 71% of the three-year-observed firms were sole proprietorships, compared to the 59% among the survivors. In the surviving firms, there were founders working that had a higher industry experience and more often a university degree. In contrast to the German firms, the US start-ups show much less mean differences during the initial three-year period of 2004-2006 (see Table 5.7). The surviving US firms had more frequently a comparative advantage (69%) as compared to the firms that could not be observed anymore after the initial three years (61%). However, similar to the German sample there are significant differences across the founder characteristics. Both tables indicate a likely survivorship bias that seems to be more essential for the German than for the US sample. Table 5.A.7 presents the corresponding estimates. Overall, the mean differences identified in Table 5.6 and Table 5.7 are related to only weak differences in the estimated coefficients' effect on employment growth. This holds for the German as well as for the US sample.

Table 5.7: Descriptive statistics (t-tests) for US start-ups, restricted to the years 2004-2006

USA	Observed only the first 3 years N = 926		Observed the whole period N = 3,351		
	Mean	Std.dev.	Mean	Std.dev.	p-value
Dependent var.:					
ln_empgr	0.165	0.598	0.160	0.523	0.81
Firm vars.:					
ln_emp	0.82	0.83	0.79	0.81	0.29
ln_age	0.89	0.20	0.89	0.20	1.00
debt	0.78	0.42	0.78	0.41	0.75
delinq	0.75	0.44	0.77	0.42	0.13
compad	0.61	0.49	0.69	0.46	0.00
sole	0.30	0.46	0.31	0.46	0.55
corp	0.30	0.46	0.31	0.46	0.67
partner	0.05	0.21	0.04	0.19	0.28
llc	0.35	0.48	0.34	0.47	0.58
team	0.35	0.48	0.33	0.47	0.25
metro	0.85	0.35	0.83	0.38	0.04
cati	0.46	0.50	0.31	0.46	0.00
Founder vars.:					
ln_experience	2.33	0.93	2.49	0.91	0.00
founded_before	0.42	0.49	0.47	0.50	0.01
degree	0.54	0.50	0.62	0.49	0.00
female	0.34	0.47	0.34	0.47	0.68

Source: KFS; authors' own calculation.

In addition, we conducted the same tests on mean differences for our subset of manufacturing firms. Table 5.A.8 and Table 5.A.9 present the results of the corresponding t-tests. Among the German manufacturing start-ups there are only three indicators (*sole*, *llc*, *female*) still significantly different in their mean values. However, the differences are only weakly significant at the 5% and 10% level, respectively. In our KFS sample, there remains only *partner* and *cati* significant. As there are only a few dozens of partnerships among the US manufacturing start-ups, the significantly different distribution across survivors and non-survivors should not cause a considerable survivorship bias. In total, we may have some survivorship issues but they are not only negligible for the general US sample but also for the US and German start-ups of the manufacturing sector. As our estimates largely coincide between the general and the manufacturing firm samples, we do not expect our findings to be substantially unreliable.

In addition, we also performed Heckman selection models to differentiate the non-response firms from the firms that could not be observed anymore after year t due to firm exit. We used this information to create a binary indicator for our selection equation. Hence, this variable takes on the value one if the firm was not participating after year t anymore but was still alive in year t+1. It takes on the value zero if the firm was not participating anymore after year t due to firm exit in year t+1. In so doing, we can distinguish those firms that exited from those firms that survived but did not participate anymore due to other reasons.[73] Using selection models reliably requires good exclusion restrictions. That is, variables that influence the sample selection but do not affect the second stage, which is employment growth in our case. Finding exclusion restrictions in case of start-ups may be particularly difficult as it may be hard to imagine any variables that do affect the start-ups' survival but not their firm growth. For start-ups, survival and growth are not overly different, for R&D-intensive start-ups in specific.

We use a set of three exclusion restrictions. As *ln_experience* and *degree* do not have a significant effect on employment growth (see Table 5.2) but are significantly different in their mean values between the 8-year survivors and the non-observed (see Table 5.6 and Table 5.7), we use these two variables as exclusion restrictions. Furthermore, we use a binary indicator measuring whether or not at least one of the founders is of German nationality, *german_native*. We think that the ability to (properly) speak German and to be able to understand the legal documents and requirements can be essential for a start-up to survive but do not necessarily determine its growth. For the US sample we tried similar indicators, however, we were less successful. Unfortunately, there are only several hundreds of observations regarding whether or not the start-ups have had at least one US citizen among their founders in 2004. Further, an indicator referring to at least one founder who was born in the USA was negatively related to start-up survival. The same appears for a variable distinguishing white from non-white founders. At the end, we created an indicator taking on the value one if none of the founders is black (or African American) or a Latino, and zero otherwise.[74] This variable is labeled as *no_minority*.

Table 5.8 presents the Heckman selection models for the German start-ups. We performed four specifications. Model XIII includes those variables that are available for the whole period of 2005-2012 to examine whether the general SUP sample suffers from a survivor bias or not. With respect to the exclusion restrictions, as expected, each of the three indicators has a positive and strong effect on firm survival. In principle, the LR-test of rho = 0 tests whether the error terms of the selection and growth equation are correlated with each other or not. In our case, finding no support for the null hypothesis indicates a significant survivorship bias. This result supports the conclusion about a potential survivorship bias drawn from the mean differences presented in Table 5.6. However, this bias vanishes when focusing on manufacturing firms (model XIV). The corresponding LR-test does not support a selection problem, which is similar to the conclusion drawn from Table 5.A.8. Model XV represents our baseline specification (model I) estimated by a selection model. In this case, we also do not find significant support for a potential survivorship bias, neither do we for the manufacturing firms (model XVI, representing model VII). Note that the models (and numbers of observations) we use for our analysis do not even include 10% of non-surviving (exiting) observations, which makes a survivorship bias (even) more unlikely.

[73] For the German case, we used Creditreform data on firm exit. For the US case, we used the KFS data that include information on firm exit as well, even though they are much less precise than the German data.

[74] Please note that we would not use the labels "black" and "white" but the KFS questionnaires are using this terminology.

Table 5.8: Heckman selection models for German start-ups

Dep. var.: ln_empgr	XIII	XIV	XV	XVI
Estimates of the growth equation:				
rnd			**0.003****	**0.007****
			(0.001)	(0.003)
gdpgr_at_t	**0.006*****	0.006	**0.004***	**0.009***
	(0.002)	(0.004)	(0.002)	(0.006)
ln_emp	**-0.095*****	**-0.095*****	**-0.124*****	**-0.127*****
	(0.008)	(0.016)	(0.012)	(0.026)
ln_capstockgr			**0.067*****	**0.162*****
			(0.019)	(0.056)
capstockmiss			**-0.363****	
			(0.148)	
ln_age	-0.027	**-0.066***	0.014	-0.007
	(0.017)	(0.037)	(0.037)	(0.080)
debt			0.015	**0.072***
			(0.020)	(0.043)
delinq	**-0.055***	0.007	-0.021	-0.000
	(0.031)	(0.070)	(0.041)	(0.113)
delinqmiss	-0.014	-0.016	-0.073	0.046
	(0.016)	(0.034)	(0.053)	(0.132)
compad	0.018	**0.091****	0.021	-0.010
	(0.018)	(0.043)	(0.029)	(0.070)
sole	**0.089*****	**0.086***	**0.087****	0.055
	(0.023)	(0.051)	(0.035)	(0.079)
llc	**0.179*****	**0.154*****	**0.132*****	**0.146****
	(0.021)	(0.048)	(0.033)	(0.073)
team	**0.152*****	**0.142*****	**0.181*****	**0.150****
	(0.017)	(0.036)	(0.026)	(0.059)
metro	**0.027****	0.019	0.021	0.035
	(0.011)	(0.024)	(0.017)	(0.040)
east	0.002	0.001	-0.019	-0.010
	(0.014)	(0.031)	(0.022)	(0.051)
founded_before	-0.009	**-0.048***	0.005	-0.038
	(0.012)	(0.027)	(0.019)	(0.045)
female	**-0.040*****	**-0.091****	0.002	0.006
	(0.015)	(0.043)	(0.025)	(0.085)
Constant	0.005	0.048	-0.010	0.039
	(0.044)	(0.093)	(0.088)	(0.178)
Estimates of the exclusion restrictions:				
ln_experience	**0.183*****	0.081	**0.434*****	0.347
	(0.029)	(0.079)	(0.069)	(0.234)
degree	**0.153*****	**0.517*****	0.128	0.191
	(0.045)	(0.137)	(0.092)	(0.309)
german_nationality	**0.155****	**0.894*****	0.191	0.620
	(0.075)	(0.196)	(0.170)	(0.542)
Observations	6,320	1,274	2,386	471
Censored obs.	957	161	233	37
Log-likelihood	-4576	-876.4	-1528	-261.2
Industry dummies (chi2):	**74.10*****	0.880	**33.42****	**4.940***
Rho	0.595	0.355	0.0593	-0.0589
LR-test rho = 0 (p):	**0.000*****	0.145	0.651	0.869

Source: SUP; authors' own calculation.

Note: *** p<0.01, ** p<0.05, * p<0.1; standard errors in parentheses; or our selection equations, we included the same variables used in the growth equation and only added the three respective exclusion restrictions to them; for reasons of clarity, we left out all the estimates of the control variables of the selection equations from the table.

The Appendix includes the estimates of models XIII to XVI for the US-American start-ups (see Table 5.A.10). Unfortunately, the set of exclusion restrictions does not seem to be as reliable as in the German case. Even though there may be some more indication to a survivorship bias than for the German start-ups, the overall conclusion of a negligible survivorship bias (if at all) for the US firms of our estimation sample (and manufacturing subsample) does not change. Overall, we do not think that our estimates suffer from a (serious) survivorship bias.

5.4.6 Instrumental variable regressions

By relying on indicators based on R&D expenditures, we can only measure the "formal" R&D activities. We may underestimate the growth effects of R&D efforts because these activities are more often informally organised than in established firms (McKelvie et al., 2013). This means that we may have an endogeneity problem requiring us to model the selection of firms into formal R&D activities (measured as R&D intensity in our case). For this reason, we also include two tables of IV regressions that treat our R&D indicator as endogenous explanatory variable. The main issue in using the IV approach in our case is to find proper instruments. That is, we would need at least one variable that is correlated with the R&D intensity but not correlated with the error term. Hence, the instrumental variable(s) is (are) not allowed to have any direct effect on the start-ups' employment growth, only a partial effect through R&D would be legitimate. Unfortunately, so far we could not find any reliable instruments. Therefore, we use an approach by Lewbel (2012) who developed an instrumental variable estimator that identifies structural parameters in the absence of traditional external instruments. Identification is achieved by having regressors that are uncorrelated with the product of heteroskedastic errors (see Lewbel, 2012 for details).

Table 5.9 presents the estimates and the corresponding tests of the IV estimations for Germany. Models XVII and XIX refer to firms of all sectors, while the other two models refer to manufacturing firms only. The estimated coefficients are very similar to the results of Table 5.2, Table 5.A.4, Table 5.A.5 and Table 3.A.3 for the German sample. Hence, we may do not have substantial endogeneity issues with our main explanatory variable. In addition, the displayed p-values of each model's exogeneity test support the null hypothesis of *rnd* being an exogenous variable. Furthermore, the Hansen J test's null hypothesis of instrument validity cannot be rejected. In addition, the Kleibergen-Paap LM test and the F test on excluded instruments do not show evidence for the instruments to be either irrelevant or weak. However, at least in model XVII, the test statistic of the Anderson-Rubin Wald test implies that the endogenous explanatory variable, *rnd*, is not significant for employment growth.

In Table 5.10, the estimates and tests of the same models estimated for the US-American sample are presented. The displayed estimates are very similar to the estimates of the pooled OLS regressions, like in the German sample. The IV-related tests indicate neither *rnd* to be endogenous nor the instruments to be invalid or weak.

These results imply that the estimates based on pooled OLS regressions are not subject to substantial endogeneity problems. However, having strong and convincing external instruments would be the most appropriate approach to test and control for potential endogeneity of *rnd*.

Table 5.9: IV regressions (based on Lewbel, 2012), German sample

Dep. var.: ln_empgr	XVII	XVIII	XIX	XX
Estimates of the growth equation:				
rnd	**0.004****	**0.007****		
	(0.002)	(0.003)		
rnd_diff			0.004	-0.003
			(0.004)	(0.005)
gdpgr_at_t	0.003	0.008	**0.006***	0.011
	(0.002)	(0.006)	(0.003)	(0.007)
ln_emp	**-0.125*****	**-0.143*****	**-0.121*****	**-0.167*****
	(0.015)	(0.024)	(0.017)	(0.033)
ln_capstockgr	**0.043***	**0.153****	0.017	**0.269*****
	(0.023)	(0.065)	(0.020)	(0.077)
capstockmiss	-0.091	**0.345*****		
	(0.210)	(0.096)		
ln_age	0.023	0.006	-0.048	-0.088
	(0.031)	(0.071)	(0.065)	(0.141)
debt	0.016	0.057	0.032	**0.103****
	(0.019)	(0.040)	(0.023)	(0.050)
delinq	-0.019	-0.135	-0.057	-0.097
	(0.043)	(0.149)	(0.040)	(0.189)
delinqmiss	-0.057	0.021	-0.007	-0.039
	(0.048)	(0.089)	(0.049)	(0.131)
compad	0.019	0.001	0.029	-0.029
	(0.023)	(0.075)	(0.034)	(0.114)
sole	**0.086****	0.074	**0.139*****	0.111
	(0.035)	(0.072)	(0.043)	(0.101)
llc	**0.129*****	**0.189*****	**0.172*****	**0.233****
	(0.032)	(0.065)	(0.041)	(0.098)
team	**0.190*****	**0.187*****	**0.199*****	**0.155****
	(0.031)	(0.056)	(0.040)	(0.072)
metro	0.023	0.024	0.026	0.090
	(0.017)	(0.039)	(0.019)	(0.055)
east	-0.023	-0.019	-0.009	0.005
	(0.019)	(0.053)	(0.019)	(0.062)
ln_experience	-0.014	-0.003	**-0.052*****	-0.088
	(0.015)	(0.042)	(0.018)	(0.062)
founded_before	-0.005	-0.069	0.001	-0.056
	(0.019)	(0.046)	(0.021)	(0.065)
degree	-0.005	-0.052	0.000	-0.019
	(0.017)	(0.047)	(0.019)	(0.064)
female	0.000	-0.015	-0.038	-0.016
	(0.022)	(0.058)	(0.025)	(0.074)
Constant	0.036	0.046	0.235	0.471
	(0.075)	(0.188)	(0.144)	(0.351)
Observations	2,386	471	1,388	266
R2_adjusted	0.063	0.089	0.066	0.103
Industry dummies (chi2):	**20.89****	0.240	**13.71***	**3.560***
IV tests:				
Test on exogeneity (p):				
rnd	0.733	-	0.897	0.381
Test on instrument validity Hansen J test (p):	0.981	-	0.384	0.754
Test on underidentification Kleibergen-Paap LM test (chi2):	**67.16*****	-	**56.31*****	**28.09***
Test on weak instruments F test on excluded instruments (F):	**106.8*****	-	**1316*****	**1265*****
Inference robust to weak identific. Anderson-Rubin Wald test (chi2):	32.80	-	**121.3*****	**33.10****

Source: SUP; authors' own calculation.

Note: *** p<0.01, ** p<0.05, * p<0.1; standard errors in parentheses are clustered at the firm level; there are no IV tests available for model XVIII.

Table 5.10: IV regressions (based on Lewbel, 2012), US sample

Dep. var.: ln_empgr	XVII	XVIII	XIX	XX
Estimates of the growth equation:				
rnd	**0.002***	0.000		
	(0.001)	(0.003)		
rnd_diff			0.004	0.006
			(0.003)	(0.005)
gdpgr_at_t	**0.008****	**0.027*****	0.005	**0.031*****
	(0.003)	(0.008)	(0.004)	(0.011)
ln_emp	**-0.139*****	**-0.064*****	**-0.127*****	**-0.047*****
	(0.009)	(0.017)	(0.010)	(0.016)
ln_capstockgr	0.002	**0.008***	0.001	0.006
	(0.001)	(0.005)	(0.002)	(0.006)
capstockmiss	**-0.029*****	-0.002		
	(0.010)	(0.038)		
ln_age	0.040	0.035	0.106	-0.051
	(0.032)	(0.085)	(0.080)	(0.216)
debt	0.017	**0.067****	**0.025****	0.044
	(0.011)	(0.034)	(0.012)	(0.041)
delinq	**-0.020****	0.000	**-0.027****	-0.016
	(0.010)	(0.026)	(0.011)	(0.027)
delinqmiss	**-0.039*****	-0.033	**-0.028***	-0.036
	(0.014)	(0.040)	(0.016)	(0.043)
compad	**0.046*****	0.007	**0.045*****	0.004
	(0.009)	(0.023)	(0.011)	(0.026)
sole	-0.011	0.032	-0.018	-0.071
	(0.023)	(0.060)	(0.024)	(0.073)
corp	0.036	0.087	0.014	-0.025
	(0.023)	(0.055)	(0.023)	(0.071)
llc	0.009	0.059	-0.008	-0.063
	(0.023)	(0.057)	(0.023)	(0.071)
team	**0.158*****	**0.109*****	**0.165*****	**0.100*****
	(0.014)	(0.035)	(0.016)	(0.034)
metro	**0.022****	-0.006	**0.022***	-0.002
	(0.010)	(0.028)	(0.012)	(0.029)
cati	**0.030*****	0.031	**0.052*****	0.050
	(0.011)	(0.031)	(0.013)	(0.034)
ln_experience	0.002	-0.002	-0.006	0.010
	(0.006)	(0.019)	(0.008)	(0.021)
founded_before	0.002	0.019	0.007	0.013
	(0.008)	(0.023)	(0.010)	(0.025)
degree	-0.007	0.022	-0.002	0.025
	(0.009)	(0.024)	(0.010)	(0.026)
female	**-0.038*****	-0.026	**-0.034*****	0.002
	(0.009)	(0.027)	(0.010)	(0.025)
Constant	-0.016	-0.161	-0.123	0.079
	(0.070)	(0.173)	(0.160)	(0.435)
Observations	7,291	952	5,106	657
R2_adjusted	0.075	0.038	0.067	0.038
Industry dummies (chi2):	**25.52*****	0.0700	**19.55****	0.200
IV tests:				
Test on exogeneity (p):				
rnd	0.270	0.660	0.799	-
Test on instrument validity				
Hansen J test (p):	0.208	0.447	0.716	0.397
Test on underidentification				
Kleibergen-Paap LM test (chi2):	**70.49*****	**38.24*****	**75.23*****	**41.98*****
Test on weak instruments				
F test on excluded instruments (F):	**83.35*****	**155.2*****	**57.24*****	**69.63*****
Inference robust to weak identific.				
Anderson-Rubin Wald test (chi2):	**47.57****	**44.52*****	**39.64***	22.96

Source: KFS; authors' own calculation.

Note: *** p<0.01, ** p<0.05, * p<0.1; standard errors in parentheses are clustered at the firm level; there are no exogeneity test available for model XX.

5.4.7 Limitations

The estimation of employment growth effects of R&D investment for start-ups is subject to potential pitfalls and shortcomings. The "traditional" channel relating R&D to growth is for firms to have e.g. successful product innovations. We do not observe any types of innovations and just assume that R&D leads to successful innovations, on average. Choosing a one-year lagged R&D indicator – as we do – may not accurately capture the lags that exist between the timing of R&D expenditures, the implementation of new products/processes and their potential success, which ultimately induces firm growth. However, as discussed in Section 5.2.1 start-ups are eager to build absorptive capacity by R&D investment, which allows them to grow not only by innovations directly. In this respect, higher R&D investment may lead to higher labour demand just because there may be new research projects requiring more employees. By using employment growth as indicator, the growth effect of R&D does not necessarily require the firms to have (new) products.

Our analysis is restricted to one specific cohort of each country. Therefore, we have to be cautious in interpreting our results as general start-up effects. It can be that younger or older cohorts in Germany and the US show different growth effects of R&D. For instance, Sedlacek and Sterk (2014) and Lee and Mukoyama (2015) find that the post-entry performance of start-ups significantly depends on the macroeconomic condition at the entry time.

Another limitation relates to the comparability of the results. Unfortunately, we do not have two perfectly comparable data sets of two countries. The main differences are discussed in Sections 5.3.1.3 and 5.3.3.4. In addition, both economies differ in terms of, for instance, public support schemes, labour market protection, the tax systems and bankruptcy laws. However, the legal forms of both countries (sole proprietorships, partnerships, corporations and limited liability companies) overlap with respect to the minimum number of owners, the rules of owner liability, the taxation of profits and losses and the disclosure requirements. Furthermore, the differences in the flexibility of both labour markets may be less relevant for our analysis. Indeed, the German labour market is more rigid than the American market. However, according to the updated version of the small firm clause ("Kleinbetriebsklausel") of 2004, the employment protection act does not apply to firms having less than 11 full-time employees. This indicates that the German start-ups can quite flexibly decide on hiring and firing just like in the US.[75]

5.5 Conclusion

We investigate the job-creating effect of start-ups' R&D investment over the business cycle. In particular, we examine whether or not higher R&D investment during the recession of 2008/2009 has led to higher employment growth among start-ups. To circumvent the one-country problem, our estimations use comparable start-up panel data sets of two of the most important economies in the world, i.e. Germany and the USA. The German sample is based on the KfW/ZEW Start-Up Panel (SUP) and covers the period of 2005-2012, whereas the US sample draws on the Kauffman Firm Survey (KFS) and includes the years 2004-2011.

The estimation results show that start-ups' R&D investment has a job-creating effect across the business cycle. This effect is positive and significant in the German sample but it is insignificant in the US sample, even though the effect is positive as well. Our results show that counter-cyclical R&D investment can have a positive effect on start-ups' employment growth. Although we do not find significant effects for our general firm samples, the findings for manufacturing firms indicate that higher R&D investment during the most recent

[75] Note that the average number of full-time equivalents is about 4 in the German (and the US) sample.

recession could significantly induce employment growth in German and US start-ups. However, there is a difference between the German and the US start-ups concerning the counter-cyclical effect. In Germany, a higher R&D investment level during the recession is significantly related to subsequent job creation. In contrast, the US start-ups could induce employment growth if they directly invested more money to finance their R&D projects. This difference indicates two distinct perspectives. In Germany, the industry perspective may be more important than the firm perspective. This means, if the industry was focussed more intensively on R&D activities particularly during recessions, German start-ups would benefit from this orientation, on average. In the US, the start-ups could only benefit from higher employment growth after the recession if they increased their individual R&D investment. Despite this difference, the overall conclusion of our analysis stays the same. R&D investment during recessions will be rewarded in terms of employment growth afterwards. Therefore, it may not be optimal for start-ups to decrease their R&D investment in this situation. This particularly holds for start-ups of the manufacturing sector.

Our results support the notion that innovative start-ups are beneficial to the dynamics of economic development. We cannot answer the question whether or not innovative start-ups are more or less successful market players than established firms. Rather, our findings indicate that R&D-conducting newly founded firms can significantly create jobs, even though we cannot observe potential downsizing at established firms triggered by those start-ups. Hence, governments aiming at developing a more entrepreneurial-oriented economy should consider the implementation or extension of R&D support schemes for start-ups particularly during recessions.

This chapter has some limitations (see Section 5.4.7). Therefore, we think our results would be more reliable if we observed different start-up cohorts of different countries over a longer period. For this reason, our results have to be interpreted cautiously. We recommend to not directly comparing the estimates' magnitudes between both countries but rather the directions of the effects.

5.A Appendix

Table 5.A.1: Variables' definitions and potential country differences

Dependent var.:		Country differences in the definitions?
ln_empgr	(Log of the number of full-time equivalents at t) - (Log of the number of full-time equivalents at t-1)	X
Independent vars.:		
rnd	(R&D expenditures / number of full-time equivalents) at t-1	X
gdpgr	Annual GDP growth between t-1 and t-2	X
gdpgr_at_t	Annual GDP growth between t and t-1	X
rnd_gdpgr	rnd * gdpgr	X
gvaindgr	Annual gross value added growth (GVA) on an industry level between t-1 and t-2	X
gvaindgr_at_t	Annual gross value added growth (GVA) on an industry level between t and t-1	X
rnd_gvaindgr	rnd * gvaindgr	X
rnd_diff	rnd_t-1 - rnd_t-2	X
rnd_diff_gdpgr	rnd_diff * gdpgr	X
rnd_diff_gvaindgr	rnd_diff * gvaindgr	X
Controls:		
Firm vars.:		
ln_emp	Log of the number of full-time equivalents at t-1	X
ln_capstockgr	Log(capital stock + 1 €/$ at t-1) - Log(capital stock + 1 €/$ at t-2)	YES
capstockmiss	Missing value dummy of ln_capstockgr	X
ln_age	Log of the age of the firm at t	X
debt	Did the firm raise external capital at t-1?	YES
delinq	Was the firm very likely to default at t-1?	YES
delinqmiss	Missing value dummy of delinq	X
compad	Did the firm have a comparative advantage at t?	YES
sole	Was the firm a sole proprietorship at t?	YES
partner	Was the firm a partnership at t?	YES
corp	Was the firm a corporation at t?	YES
llc	Was the firm a limited liability company at t?	YES
team	Was the firm run by a team of actively involved owners at t?	X
metro	Was the firm located in a metropolitan area at t?	YES
east	Was the firm located in Eastern Germany at t?	YES
kfw	Did the firm receive financial support by the KfW at t?	YES
cati	Did the firm complete the questionnaire via telephone at t?	YES
Founder vars.:		
ln_experience	The log of the years of industry experience of the founder with the longest experience	X

founded_before	Has at least one founder ever started a firm before?	X
degree	Has at least one of the founders obtained at least a bachelor degree?	X
female	Was the business (co-)founded by women?	X
german_native	Is at least one of the founders a German native?	YES
no_minority	Are no black and no latino people among the founders?	YES

Source: KfW/ZEW Start-Up Panel (SUP) and the Kauffman Firm Survey (KFS); authors' own calculations.
Note: We omitted the industry dummies from this table for reasons of clarity; the included industry dummies differ between the SUP sample and the KFS sample due to the different underlying industry classification systems (NACE vs. NAICS).

Table 5.A.2: Descriptive statistics of the subset of manufacturing firms

Variables	Germany				USA	
Dependent var.:	Mean	Std. dev.	Min	Max	Mean	Std. dev.
ln_empgr	0.06	0.41	-1.45	1.39	-0.01	0.39
Independent vars.:						
rnd	2.32	6.63	0	49.0	2.39	6.16
gdpgr	1.47	3.34	-5.6	4.10	0.30	2.01
gdpgr_at_t	0.38	3.43	-5.6	4.10	0.10	2.03
rnd_gdpgr	3.31	25.88	-240	162	0.36	13.78
gvaindgr	1.76	10.93	-19.3	18.6	-0.55	4.92
gvaindgr_at_t	-0.72	12.32	-19.3	18.6	-1.54	4.70
rnd_gvaindgr	4.41	63.78	-576	449	-2.09	34.13
Controls:						
Firm vars.:						
ln_emp	1.26	0.84	0	4.62	1.33	1.10
ln_capstockgr	0.13	0.33	-0.11	2.04	0.00	2.69
capstockmiss	0.00	0.05	0	1	0.13	0.34
ln_age	1.67	0.25	1.39	2.08	1.84	0.17
debt	0.29	0.45	0	1	0.80	0.40
delinq	0.04	0.19	0	1	0.54	0.50
delinqmiss	0.02	0.15	0	1	0.09	0.29
compad	0.92	0.27	0	1	0.56	0.50
sole	0.55	0.50	0	1	0.22	0.41
partner	0.11	0.32	0	1	0.02	0.15
corp					0.47	0.50
llc	0.34	0.47	0	1	0.29	0.45
team	0.30	0.46	0	1	0.43	0.50
metro	0.56	0.50	0	1	0.83	0.37
east	0.20	0.40	0	1		
cati					0.23	0.42
Founder vars.:						
ln_experience	2.89	0.54	1.39	3.93	2.91	0.65
founded_before	0.31	0.46	0	1	0.52	0.50
degree	0.26	0.44	0	1	0.55	0.50
female	0.11	0.32	0	1	0.32	0.47

Source: SUP (Germany) and KFS (USA); authors' own calculation.
Note: The number of observations for the German sample is 471 and for the US sample 952; due to confidentiality reasons we are not allowed to present the min and max values for the US sample; we are also not allowed to present the values of the kfw dummy variable.

Table 5.A.3: Descriptive statistics of the regressions on the annual difference of the R&D intensity, *rnd_diff*

Variables	Germany				USA	
Dependent var.:	Mean	Std. dev.	Min	Max	Mean	Std. dev.
ln_empgr	0.02	0.37	2.08	2.08	-0.02	0.40
Independent vars.:						
rnd_diff	-0.12	3.89	25.9	26.9	-0.13	2.36
gdpgr	0.60	3.61	-5.6	4.10	-0.27	2.11
gdpgr_at_t	-0.44	4.33	-5.6	4.10	0.28	2.37
rnd_diff_gdpgr	-0.09	14.43	-151	145	0.01	4.87
gvaindgr	0.46	6.31	19.3	18.6	-0.99	3.93
gvaindgr_at_t	-0.41	7.19	19.3	18.6	-0.31	3.92
rnd_diff_gvaindgr	-0.44	27.34	-519	281	0.01	10.14
Controls:						
Firm vars.:						
ln_emp	0.98	0.85	0	3.74	0.87	0.94
ln_capstockgr	0.11	0.51	0.11	11.71	-0.05	3.68
capstockmiss	0.00	0.07	0	1	0.27	0.45
ln_age	1.80	0.18	1.61	2.08	1.93	0.12
debt	0.25	0.43	0	1	0.76	0.43
delinq	0.05	0.21	0	1	0.54	0.50
delinqmiss	0.02	0.15	0	1	0.13	0.34
compad	0.91	0.28	0	1	0.46	0.50
sole	0.64	0.48	0	1	0.31	0.46
partner	0.11	0.31	0	1	0.03	0.17
corp					0.32	0.47
llc	0.25	0.43	0	1	0.33	0.47
team	0.21	0.41	0	1	0.28	0.45
metro	0.64	0.48	0	1	0.82	0.38
east	0.20	0.40	0	1		
cati					0.22	0.41
Founder vars.:						
ln_experience	2.82	0.54	1.61	3.89	2.88	0.59
founded_before	0.32	0.47	0	1	0.46	0.50
degree	0.43	0.49	0	1	0.60	0.49
female	0.14	0.35	0	1	0.34	0.47
Industries:						
High-tech manufacturing	0.08	0.27	0	1	0.06	0.23
Non-high-tech manufacturing	0.12	0.32	0	1	0.08	0.27
Technical services	0.26	0.44	0	1	0.09	0.29
Software	0.08	0.28	0	1	0.02	0.14
Knowledge-intens. services	0.07	0.25	0	1	0.08	0.27
Consumer-oriented services	0.13	0.34	0	1	0.22	0.41
Other services	0.03	0.18	0	1	0.19	0.39
Construction	0.12	0.32	0	1	0.08	0.27
Wholesale/retail	0.12	0.32	0	1	0.16	0.37

Source: SUP (Germany) and KFS (USA); authors’ own calculation.
Note: The number of observations for the German sample is 1,388 and for the US sample 5,106; due to confidentiality reasons we are not allowed to present the min and max values for the US sample; we are also not allowed to present the values of the kfw dummy variable.

Table 5.A.4: Full table of Table 5.3

	Germany			USA		
Dep. var.: ln_empgr	IV	V	VI	IV	V	VI
rnd_diff	0.003	0.003	0.003	0.001	0.001	0.001
	(0.003)	(0.003)	(0.004)	(0.003)	(0.003)	(0.003)
rnd_diff_gdpgr		0.000			-0.001	
		(0.001)			(0.001)	
gdpgr		-0.005			0.004	
		(0.005)			(0.003)	
gdpgr_at_t	**0.006***	0.002		0.005	**0.010*****	
	(0.003)	(0.004)		(0.004)	(0.002)	
rnd_diff_gvaindgr			-0.000			-0.000
			(0.000)			(0.001)
gvaindgr			-0.002			0.000
			(0.002)			(0.002)
gvaindgr_at_t			0.002			**0.006****
			(0.002)			(0.002)
Controls:						
ln_emp	**-0.123*****	**-0.123*****	**-0.124*****	**-0.128*****	**-0.127*****	**-0.128*****
	(0.018)	(0.018)	(0.018)	(0.010)	(0.010)	(0.010)
ln_capstockgr	**0.059****	**0.059****	**0.059****	0.001	0.001	0.001
	(0.026)	(0.026)	(0.026)	(0.002)	(0.002)	(0.002)
capstockmiss	**-0.560****	**-0.557****	**-0.562****	-0.007	-0.007	-0.007
	(0.272)	(0.275)	(0.274)	(0.012)	(0.012)	(0.012)
ln_age	-0.045	0.055	0.045	0.105		0.083
	(0.066)	(0.108)	(0.063)	(0.080)		(0.073)
debt	0.030	0.029	0.029	**0.024***	**0.024***	**0.025****
	(0.023)	(0.023)	(0.023)	(0.013)	(0.013)	(0.013)
delinq	-0.060	-0.060	-0.059	**-0.026****	**-0.026****	**-0.026****
	(0.040)	(0.040)	(0.040)	(0.011)	(0.012)	(0.011)
delinqmiss	0.021	0.021	0.022	**-0.027***	**-0.028***	-0.027
	(0.055)	(0.055)	(0.055)	(0.016)	(0.017)	(0.017)
compad	0.029	0.029	0.028	**0.045*****	**0.045*****	**0.046*****
	(0.034)	(0.034)	(0.034)	(0.011)	(0.011)	(0.011)
sole	**0.141*****	**0.141*****	**0.141*****	-0.017	-0.017	-0.017
	(0.043)	(0.043)	(0.044)	(0.024)	(0.024)	(0.024)
corp				0.014	0.014	0.015
				(0.023)	(0.023)	(0.023)
llc	**0.174*****	**0.174*****	**0.174*****	-0.008	-0.008	-0.008
	(0.041)	(0.041)	(0.041)	(0.023)	(0.023)	(0.023)
team	**0.200*****	**0.200*****	**0.200*****	**0.165*****	**0.165*****	**0.165*****
	(0.040)	(0.040)	(0.040)	(0.016)	(0.016)	(0.016)
metro	0.024	0.024	0.024	**0.023***	**0.023***	**0.023***
	(0.019)	(0.018)	(0.019)	(0.012)	(0.012)	(0.012)
east	-0.011	-0.011	-0.011			
	(0.019)	(0.019)	(0.019)			
cati				**0.052*****	**0.052*****	**0.052*****
				(0.013)	(0.013)	(0.013)
ln_experience	**-0.053*****	**-0.053*****	**-0.054*****	-0.006	-0.006	-0.006
	(0.018)	(0.018)	(0.018)	(0.008)	(0.008)	(0.008)
founded_before	0.000	0.001	0.001	0.007	0.007	0.007
	(0.021)	(0.021)	(0.021)	(0.010)	(0.010)	(0.010)
degree	-0.003	-0.003	-0.003	-0.002	-0.001	-0.001
	(0.019)	(0.019)	(0.019)	(0.010)	(0.010)	(0.010)
female	-0.029	-0.028	-0.030	**-0.034*****	**-0.034*****	**-0.033*****
	(0.025)	(0.025)	(0.025)	(0.010)	(0.010)	(0.010)
Constant	0.230	0.051	0.070	-0.122	**0.082***	-0.074
	(0.146)	(0.212)	(0.135)	(0.160)	(0.045)	(0.151)
Observations	1,388	1,388	1,388	5,106	5,106	5,106
R2_adjusted	0.072	0.072	0.070	0.067	0.067	0.068
Industry dummies (F):	1.610	1.610	1.580	**2.010****	**2.010****	**2.220****

Source: SUP (Germany) and KFS (USA); authors' own calculation.
Note: *** p<0.01, ** p<0.05, * p<0.1; standard errors – in parentheses – are clustered at the firm level.

Table 5.A.5: Full table of Table 5.4

	Germany			USA		
Dep. var.: ln_empgr	VII	VIII	IX	VII	VIII	IX
rnd	**0.007****	**0.009*****	**0.007****	0.003	0.002	0.003
	(0.003)	(0.003)	(0.003)	(0.002)	(0.002)	(0.002)
rnd_gdpgr		**-0.002*****			0.002	
		(0.001)			(0.001)	
gdpgr		-0.006			-0.005	
		(0.006)			(0.007)	
gdpgr_at_t	0.008	0.006		**0.027*****	**0.027*****	
	(0.007)	(0.007)		(0.008)	(0.008)	
rnd_gvaindgr			-0.000			0.001
			(0.000)			(0.000)
gvaindgr			-0.002			0.000
			(0.002)			(0.003)
gvaindgr_at_t			0.002			**0.012*****
			(0.002)			(0.004)
Controls:						
ln_emp	**-0.143*****	**-0.138*****	**-0.140*****	**-0.065*****	**-0.066*****	**-0.066*****
	(0.030)	(0.029)	(0.029)	(0.018)	(0.018)	(0.018)
ln_capstockgr	**0.153****	**0.161****	**0.162****	0.008	0.008	0.008
	(0.068)	(0.069)	(0.068)	(0.005)	(0.005)	(0.005)
capstockmiss	**0.345*****	**0.334*****	**0.353*****	-0.005	-0.004	-0.004
	(0.094)	(0.091)	(0.095)	(0.038)	(0.038)	(0.038)
ln_age	0.006	-0.013	0.010	0.038	0.038	0.056
	(0.071)	(0.070)	(0.084)	(0.086)	(0.086)	(0.083)
debt	0.057	0.061	0.059	**0.068***	**0.068***	**0.068***
	(0.040)	(0.039)	(0.039)	(0.035)	(0.035)	(0.035)
delinq	-0.135	-0.171	-0.138	0.001	0.002	0.002
	(0.143)	(0.132)	(0.140)	(0.026)	(0.026)	(0.026)
delinqmiss	0.021	0.040	0.024	-0.030	-0.031	-0.030
	(0.040)	(0.037)	(0.039)	(0.041)	(0.041)	(0.041)
compad	0.001	-0.006	-0.003	0.001	0.002	0.001
	(0.052)	(0.053)	(0.053)	(0.022)	(0.022)	(0.022)
sole	0.074	0.062	0.075	0.034	0.035	0.036
	(0.066)	(0.064)	(0.065)	(0.060)	(0.061)	(0.061)
corp				0.085	0.085	0.085
				(0.056)	(0.056)	(0.056)
llc	**0.189*****	**0.183*****	**0.187*****	0.054	0.054	0.054
	(0.065)	(0.065)	(0.065)	(0.058)	(0.058)	(0.058)
team	**0.187*****	**0.178*****	**0.188*****	**0.112*****	**0.114*****	**0.115*****
	(0.057)	(0.055)	(0.057)	(0.035)	(0.035)	(0.035)
metro	0.024	0.027	0.028	-0.009	-0.007	-0.006
	(0.038)	(0.038)	(0.038)	(0.028)	(0.028)	(0.028)
east	-0.019	-0.019	-0.020			
	(0.046)	(0.045)	(0.045)			
cati				0.034	0.033	0.033
				(0.032)	(0.032)	(0.032)
ln_experience	-0.003	-0.011	-0.011	-0.004	-0.004	-0.005
	(0.041)	(0.040)	(0.041)	(0.019)	(0.020)	(0.020)
founded_before	-0.069	**-0.079***	-0.072	0.019	0.019	0.018
	(0.048)	(0.047)	(0.048)	(0.024)	(0.024)	(0.024)
degree	-0.052	-0.034	-0.039	0.019	0.017	0.017
	(0.051)	(0.052)	(0.052)	(0.024)	(0.024)	(0.024)
female	-0.015	-0.017	-0.017	-0.026	-0.028	-0.028
	(0.052)	(0.049)	(0.051)	(0.028)	(0.028)	(0.028)
Constant	0.046	0.121	0.068	-0.160	-0.159	-0.172
	(0.174)	(0.166)	(0.186)	(0.175)	(0.176)	(0.174)
Observations	471	471	471	952	952	952
R2_adjusted	0.089	0.107	0.097	0.039	0.040	0.041
Industry dummies (F):	0.290	0.460	0.400	0.050	0.040	0.040

Source: SUP (Germany) and KFS (USA); authors’ own calculation.

Note: *** p<0.01, ** p<0.05, * p<0.1; standard errors – in parentheses – are clustered at the firm level.

Table 5.A.6: Full table of Table 5.5

	Germany			USA		
Dep. var.: ln_empgr	X	XI	XII	X	XI	XII
rnd_diff	-0.003	-0.003	-0.004	0.007	0.006	0.004
	(0.004)	(0.004)	(0.005)	(0.005)	(0.004)	(0.004)
rnd_diff_gdpgr		0.000			**-0.005****	
		(0.002)			(0.002)	
gdpgr		-0.007			-0.004	
		(0.011)			(0.007)	
gdpgr_at_t	0.011	0.005		**0.031*****	**0.028*****	
	(0.008)	(0.012)		(0.011)	(0.007)	
rnd_diff_gvaindgr			-0.000			**-0.002****
			(0.000)			(0.001)
gvaindgr			-0.002			-0.029
			(0.003)			(0.030)
gvaindgr_at_t			0.001			-0.019
			(0.003)			(0.032)
Controls:						
ln_emp	**-0.167*****	**-0.167*****	**-0.169*****	**-0.046*****	**-0.046*****	**-0.045*****
	(0.040)	(0.040)	(0.040)	(0.016)	(0.016)	(0.016)
ln_capstockgr	**0.269*****	**0.272*****	**0.276*****	0.006	0.006	0.006
	(0.079)	(0.081)	(0.079)	(0.006)	(0.006)	(0.006)
capstockmiss				0.010	0.013	0.010
				(0.044)	(0.043)	(0.043)
ln_age	-0.088	0.050	0.101	-0.046		1.708
	(0.130)	(0.248)	(0.209)	(0.219)		(1.722)
debt	**0.103****	**0.102****	**0.103****	0.045	0.049	0.049
	(0.050)	(0.050)	(0.050)	(0.042)	(0.043)	(0.042)
delinq	-0.097	-0.098	-0.096	-0.017	-0.015	-0.013
	(0.187)	(0.188)	(0.186)	(0.027)	(0.027)	(0.027)
delinqmiss	-0.039	-0.037	-0.036	-0.037	-0.039	-0.038
	(0.063)	(0.063)	(0.062)	(0.043)	(0.043)	(0.043)
compad	-0.029	-0.032	-0.029	0.004	0.000	0.001
	(0.098)	(0.099)	(0.099)	(0.027)	(0.027)	(0.027)
sole	0.110	0.109	0.109	-0.071	-0.063	-0.068
	(0.104)	(0.105)	(0.105)	(0.075)	(0.075)	(0.073)
corp				-0.023	-0.023	-0.027
				(0.073)	(0.073)	(0.071)
llc	**0.232****	**0.231****	**0.229****	-0.061	-0.061	-0.065
	(0.100)	(0.102)	(0.101)	(0.074)	(0.073)	(0.071)
team	**0.155***	**0.153***	**0.156***	**0.099*****	**0.110*****	**0.111*****
	(0.087)	(0.089)	(0.089)	(0.035)	(0.036)	(0.036)
metro	**0.090***	**0.091***	**0.090***	-0.003	-0.003	-0.005
	(0.053)	(0.053)	(0.053)	(0.030)	(0.030)	(0.030)
east	0.005	0.005	0.004			
	(0.058)	(0.058)	(0.058)			
cati				0.049	0.048	0.050
				(0.034)	(0.033)	(0.033)
ln_experience	-0.087	-0.088	-0.093	0.011	0.007	0.006
	(0.060)	(0.063)	(0.063)	(0.022)	(0.022)	(0.022)
founded_before	-0.056	-0.055	-0.053	0.012	0.016	0.015
	(0.057)	(0.058)	(0.058)	(0.026)	(0.026)	(0.026)
degree	-0.018	-0.018	-0.016	0.025	0.026	0.024
	(0.067)	(0.068)	(0.067)	(0.026)	(0.027)	(0.027)
female	-0.016	-0.014	-0.021	0.003	0.003	0.005
	(0.073)	(0.071)	(0.069)	(0.025)	(0.026)	(0.025)
Constant	0.471	0.227	0.149	0.065	-0.028	-3.382
	(0.333)	(0.481)	(0.445)	(0.441)	(0.113)	(3.403)
Observations	266	266	266	657	657	657
R2_adjusted	0.103	0.097	0.100	0.037	0.046	0.044
Industry dummies (F):	**3.710***	**3.710***	**3.570***	0.190	0.080	0.060

Source: SUP (Germany) and KFS (USA); authors' own calculation.

Note: *** p<0.01, ** p<0.05, * p<0.1; standard errors – in parentheses – are clustered at the firm level.

Table 5.A.7: Employment growth effects of the period 2005-2007 (2004-2006) for Germany (USA), differentiated by surviving and non-surviving firms

Dep. var.: ln_empgr	**Germany**		**USA**	
	observed the whole period	3 years	observed the whole period	3 years
gdpgr_at_t	**0.159***** (0.059)	0.083 (0.070)	**0.194***** (0.031)	**0.241***** (0.069)
Controls:				
ln_emp	**-0.054***** (0.018)	**-0.043**** (0.019)	**-0.217***** (0.015)	**-0.298***** (0.037)
ln_capstockgr				
capstockmiss				
debt			**-0.036*** (0.022)	0.037 (0.042)
delinq	-0.047 (0.125)	0.016 (0.065)	**-0.052*** (0.030)	-0.047 (0.061)
delinqmiss	-0.038 (0.025)	-0.004 (0.030)	0.020 (0.042)	0.022 (0.084)
compad	0.031 (0.037)	0.016 (0.035)	**0.087***** (0.017)	**0.111***** (0.037)
sole	-0.007 (0.059)	0.055 (0.050)	-0.058 (0.050)	-0.068 (0.102)
corp			0.054 (0.050)	0.124 (0.100)
llc	**0.095**** (0.043)	**0.157***** (0.048)	-0.034 (0.049)	-0.045 (0.097)
team	0.022 (0.053)	0.073 (0.045)	**0.240***** (0.026)	**0.226***** (0.054)
metro	0.031 (0.025)	0.010 (0.023)	-0.012 (0.021)	0.065 (0.045)
cati			**-0.033*** (0.020)	-0.028 (0.038)
east	0.007 (0.034)	**-0.061*** (0.031)		
ln_experience	-0.025 (0.017)	-0.006 (0.016)	0.006 (0.010)	**0.057***** (0.018)
founded_before	0.045 (0.029)	0.008 (0.032)	**0.047***** (0.017)	**0.070*** (0.040)
degree	-0.007 (0.027)	-0.006 (0.028)	-0.015 (0.019)	0.033 (0.036)
female	0.001 (0.034)	-0.020 (0.032)	**-0.093***** (0.019)	**-0.102***** (0.038)
Constant	-0.363 (0.231)	-0.135 (0.248)	**-0.200*** (0.114)	**-0.584**** (0.244)
Observations	833	916	3,351	926
R2_adjusted	0.068	0.045	0.134	0.168
Industry dummies (F):	**3.380*****	**1.820***	**3.920*****	**1.770****

Source: SUP (Germany) and KFS (USA); authors’ own calculation.

Note: *** p<0.01, ** p<0.05, * p<0.1; standard errors – in parentheses – are clustered at the firm level.

Table 5.A.8: Descriptive statistics (t-tests) for German manufacturing start-ups, restricted to the years 2005-2007

Germany	Observed only the first 3 years N = 176		Observed the whole period N = 190		
	Mean	Std.dev.	Mean	Std.dev.	p-value
Dependent var.:					
ln_empgr	0.17	0.36	0.16	0.34	0.80
Firm vars.:					
ln_emp	0.91	0.89	0.90	0.73	0.95
ln_age	0.91	0.20	0.90	0.20	0.65
delinq	0.02	0.15	0.01	0.07	0.15
compad	0.93	0.26	0.93	0.25	0.84
sole	0.61	0.49	0.51	0.50	0.05
partner	0.10	0.30	0.12	0.32	0.55
llc	0.29	0.45	0.37	0.49	0.09
team	0.26	0.44	0.32	0.47	0.21
metro	0.58	0.50	0.60	0.49	0.69
east	0.19	0.39	0.17	0.38	0.63
Founder vars.:					
ln_experience	2.60	0.72	2.66	0.71	0.42
founded_before	0.38	0.49	0.35	0.48	0.51
degree	0.24	0.43	0.28	0.45	0.39
female	0.17	0.38	0.11	0.31	0.07

Source: SUP; authors' own calculation.

Table 5.A.9: Descriptive statistics (t-tests) for US manufacturing start-ups, restricted to the years 2004-2006

USA	Observed only the first 3 years N = 124		Observed the whole period N = 528		
	Mean	Std.dev.	Mean	Std.dev.	p-value
Dependent var.:					
ln_empgr	0.229	0.642	0.242	0.535	0.81
Firm vars.:					
ln_emp	1.00	0.97	1.01	0.90	0.91
ln_age	0.87	0.20	0.87	0.20	0.95
debt	0.77	0.42	0.80	0.40	0.60
delinq	0.65	0.48	0.72	0.45	0.16
compad	0.72	0.45	0.74	0.44	0.64
sole	0.24	0.43	0.20	0.40	0.33
corp	0.41	0.49	0.45	0.50	0.45
partner	0.07	0.26	0.02	0.14	0.00
llc	0.27	0.45	0.33	0.47	0.25
team	0.43	0.50	0.45	0.50	0.72
metro	0.84	0.37	0.82	0.38	0.62
cati	0.51	0.50	0.30	0.46	0.00
Founder vars.:					
ln_experience	2.49	1.06	2.60	0.93	0.26
founded_before	0.56	0.50	0.54	0.50	0.62
degree	0.52	0.50	0.61	0.49	0.10
female	0.32	0.47	0.28	0.45	0.37

Source: KFS; authors' own calculation.

Table 5.A.10: Heckman selection models for US-American start-ups

Dep. var.: ln_empgr	XIII	XIV	XV	XVI
Estimates of the growth equation:				
rnd			**0.003****	**0.005****
			(0.001)	(0.002)
gdpgr_at_t	**0.016*****	**0.029*****	**0.009*****	**0.028*****
	(0.002)	(0.006)	(0.003)	(0.008)
ln_emp	**-0.159*****	**-0.101*****	**-0.127*****	**-0.060*****
	(0.005)	(0.012)	(0.006)	(0.015)
ln_capstockgr			**0.002***	0.006
			(0.001)	(0.005)
capstockmiss			**-0.028****	-0.023
			(0.012)	(0.040)
ln_age	0.002	**-0.105*****	**0.144*****	0.055
	(0.014)	(0.032)	(0.039)	(0.096)
debt	0.014	**0.072*****	0.018	**0.057***
	(0.010)	(0.027)	(0.012)	(0.033)
delinq	**-0.044*****	-0.014	**-0.020***	0.019
	(0.010)	(0.025)	(0.011)	(0.028)
delinqmiss	-0.006	**0.091****	**-0.038****	-0.029
	(0.014)	(0.038)	(0.016)	(0.048)
compad	**0.078*****	**0.077*****	**0.052*****	0.008
	(0.008)	(0.023)	(0.010)	(0.027)
sole	0.003	-0.098	0.012	0.028
	(0.024)	(0.077)	(0.031)	(0.104)
corp	**0.077*****	-0.033	**0.062****	0.082
	(0.023)	(0.073)	(0.030)	(0.100)
llc	0.032	-0.066	0.031	0.036
	(0.023)	(0.074)	(0.030)	(0.101)
team	**0.199*****	**0.149*****	**0.158*****	**0.118*****
	(0.011)	(0.026)	(0.013)	(0.032)
metro	**0.018***	-0.000	**0.024***	-0.010
	(0.011)	(0.029)	(0.013)	(0.036)
cati	-0.012	**0.041***	**0.025****	**0.054***
	(0.009)	(0.024)	(0.012)	(0.031)
founded_before	0.012	-0.001	-0.004	0.001
	(0.008)	(0.022)	(0.010)	(0.026)
female	**-0.073*****	**-0.089*****	**-0.047*****	-0.029
	(0.009)	(0.024)	(0.011)	(0.029)
Constant	0.024	**0.243****	**-0.264*****	-0.195
	(0.043)	(0.109)	(0.088)	(0.217)
Estimates of the exclusion restrictions:				
ln_experience	**0.103*****	**0.142*****	**0.129*****	**0.301*****
	(0.013)	(0.036)	(0.033)	(0.098)
degree	0.015	-0.071	-0.058	**-0.229***
	(0.023)	(0.066)	(0.046)	(0.137)
no_minority	0.047	**-0.237****	0.039	-0.220
	(0.032)	(0.108)	(0.066)	(0.234)
Observations	17,141	2,467	7,259	946
Censored obs.	3876	532	743	91
Log-likelihood	-15992	-2381	-5143	-616.5
Industry dummies (chi2):	**159.4*****	2.790	**54.22*****	1.370
Rho	0.609	-0.008	0.477	0.212
LR-test rho = 0 (p):	**0.012****	0.935	**0.001*****	0.340

Source: KFS; authors’ own calculation.

Note: *** p<0.01, ** p<0.05, * p<0.1; standard errors in parentheses; for our selection equations, we included the same variables used in the growth equation and only added the three respective exclusion restrictions to them; for reasons of clarity, we left out all the estimates of the control variables of the selection equations from the table; the last two estimations do not include 7,291 and 952 observations, respectively, as the information on *no_minority* is not available for all firms.

Chapter 6

Conclusion

6.1 Summary

The purpose of this dissertation was to provide empirical evidence on the efficacy of firm-level innovation over the business cycle. Each of the research chapters investigated the business cycle dependency the specific channels of the relationship of innovation and firm growth is subject to. The chapters relied on different data sources covering not only Germany but also other European countries as well as the USA to prevent a too narrow perspective. The concluding chapter summarises the main findings of this PhD project, it discusses the main implications and it reflects on the general limitations and suggests potential directions for future research.

6.2 Summary of main findings

The first study of this dissertation, presented in Chapter 2, investigated the impact of public R&D subsidies on R&D investment of small and medium-sized enterprises (SMEs) during the most recent economic crisis in Germany. The empirical analysis is based on firm-level data from the Mannheim Innovation Panel (MIP) covering the years 2006 to 2010. Chapter 2 found that SMEs generally increase their R&D investment in case they receive public subsidies. The firms increase their investment by even more than the actual amount of subsidy. However, this additionality effect could not be found for subsidies firms were receiving during the crisis in 2009. Rather, the subsidy amount crowded out the private R&D investment, which led to a lower level of R&D expenditures than a twin firm that had not received a subsidy. In 2010, when the German economy already recovered from the crisis the crowding out effect vanished and an additionality effect appeared again. Further, Chapter 2 showed that the temporary crowding out effect was caused by the subsidy recipients' R&D investment behaviour rather than by Germany's counter-cyclical subsidy policy.

In Chapter 3, we examined the link between the adjustment of innovation investment on the performance of product innovations and its business cycle dependency. The particular target was to investigate whether or not firms that increased their innovation investment during the trough year 2009 could increase their subsequent product innovation performance. Based on a MIP firm sample observed over the years 2006 to 2012, Chapter 3 showed that a pro-cyclical innovation investment is positively related to the firms' product innovation success. Even more important, the analysis found evidence for a counter-cyclical effect. That is, if the firms increased their innovation expenses during the 2008/2009 recession period, they could benefit from higher product innovation performance in the post-crisis period. This positive effect was found to be even stronger than the corresponding effect of a pro-cyclical innovation investment.

In Chapter 4, we focussed on the cyclical dependency of the employment growth effect induced by different types of innovations. Our particular target was to analyse a potential resilience of innovators in case they have to face an economic slump. The empirical analysis relied on a large sample of European manufacturing firms provided by the Community Innovation Survey (CIS). The chapter disclosed a discrepancy in the job creation ability between product innovations and process and organisational innovations. That is, the net employment growth induced by product innovations is pro-cyclical and positive during upturn, boom and downturn periods but not during recessions. When faced with an economic slump, the firms' product innovations disclose an employment-preserving, though negative effect making the innovators still more resilient than other firms. This resilience effect, however, could only be found for SMEs but not for large firms. Process and organisational innovations reduce firms' employment growth during upturns and downturns. Our results suggested that product innovations are an important driving force for job creation. They can even secure jobs during recession periods.

The last research chapter, Chapter 5, provided first evidence as to the employment growth effect of start-ups' R&D investment over the business cycle. We particularly focussed on the research question whether or not higher R&D investment during the 2008/2009 recession could induce higher employment growth among start-ups. By using the KfW/ZEW Start-Up Panel (SUP) and the Kauffman Firm Survey (KFS), as a general effect we found that start-ups' R&D investment increases the firms' employment growth. In addition, our results disclosed that a counter-cyclical R&D investment is an effective way to induce start-ups' employment growth. However, this counter-cyclical effect only becomes significant for manufacturing firms. Furthermore, the findings indicated that the R&D investment level is related to the counter-cyclical effect in Germany. In contrast, the US sample disclosed a counter-cyclical effect directly arising from a positive annual change of the R&D intensity. Hence, despite this difference, the overall conclusion for both countries' start-ups remains, i.e. counter-cyclical R&D investment induces additional employment growth.

6.3 Implications

The central findings of this thesis have a number of relevant implications for researchers and policymakers interested in the business cycle dependency of firms' innovation activities. From a research perspective, this dissertation is in contrast to prior related literature that merely investigates whether innovation investment and the implementation of innovation is pro- or counter-cyclical, respectively. Instead, this thesis focussed on the efficacy of firms' R&D subsidies, innovation in- and output over different phases of a business cycle. From a policy perspective, this thesis advances the awareness that policy programs aiming at strengthening economic growth by fostering innovation activities have to consider the timing of the respective policy initiative. The timing can be crucial as, for instance, recession periods open up new possibilities for firms to grow afterwards but also endanger the firms' survival and ability to invest in risky projects such as innovations.

Chapter 2 is a first effort to examine a country's counter-cyclical R&D public support scheme and to test whether or not it is a desirable policy initiative. In principle, the chapter suggests that R&D subsidies have the desired additionality effects on SMEs' R&D investment level. This general positive effect has already been found by previous research (see Zúñiga-Vicente et al., 2014). Hence, policymakers should generally continue the provision of R&D subsidy programs. However, the chapter also implies that policymakers may have to be more careful regarding counter-cyclical R&D support. The public funding tends to crowd out firms' R&D investment amount during severe recession periods, which leads to lower R&D investment instead of more. For this reason, it may be not recommendable to establish counter-cyclical direct support schemes in that they achieve the opposite of the desired effect. This does not necessarily mean that R&D subsidy programs should be (temporarily) stopped during recessions. Recession periods are not really predictable and public support schemes typically run over a longer period. Hence, a temporary stop of the support scheme is likely to have strong negative effects on the firms and their innovation activities. The negative additionality effect rather implies that there may be no entitlement to increase the subsidy amount as compared with non-recession years. Or, that a counter-cyclical expansion should be conducted very carefully in the sense of focusing on certain type of firms, technologies or cooperation, which may be particularly promising. Therefore, funding more firms – as during the 2009 recession – and increasing the average project funding may not be the first-best type government R&D intervention. A more selective approach may lead to a positive treatment effect during recessions after all.

In contrast to Chapter 2's more policy-oriented implications, the implications of Chapter 3's findings rather refer to the firms' management. The results suggest that product innovating firms should increase their innovation investment if they want to gain from higher product innovation success. This implication does not only hold for periods when the economy is positively growing but also for deep recession periods. In particular, counter-cyclical innovation investment leads to higher sales shares of new-to-the-market products after the recession. The effect is even stronger than the effect related to pro-cyclical innovation investment. Hence, firms planning to increase their innovation expenditures should wait for a recession to arise to be able to exploit a changed market environment in the subsequent period. From a policymaker's perspective, this would actually call for financial support for the product innovators during recessions. As we discussed earlier, a counter-cyclical R&D subsidy may not have the desired effect. However, the negative subsidy effect was found for SMEs' R&D investment. This does not necessarily hold for larger firms as well. Furthermore, policymakers could also support the innovators by establishing specific tax reliefs – a system established in other European countries like the Netherlands or Spain – that may show more desirable effects if conducted counter-cyclically than a direct subsidy support scheme.

The core findings of Chapter 4 suggest that firms should invest in the development and implementation of new products not only during upturn, boom and downturn periods but also during recession periods. In particular, product innovations have an employment preserving effect during recessions making them more resilient than non-product innovators. However, this applies only to SMEs but not to large firms. Therefore, focusing on product innovations is likely to increase the survival chance of SMEs and it enhances or at least maintains their competitive position subsequently. Large firms' product innovations do not lead to more resilience as compared to non-product innovators. This may mean that large firms (should) exploit their comparative advantage in generating process innovations during recession periods. From a policymaker's point of view, promoting the implementation of product innovations in SMEs may be particularly desirable due to their potential to stabilise the economy when facing economic slumps. In a similar line of reasoning, SMEs are typically the firms that create most of the jobs in an economy. In contrast, the implications are less straightforward for process and organisational innovations because they do not reveal a substantial negative and positive impact on the firms' employment growth, respectively. At least this means that these types of innovations are not substantially job-destructing. Unfortunately, our data did not allow us to measure the potential price effect, which is supposed to have a job-creating effect for the firms. For this reason, it may be even recommendable for large firms to focus on process and organisational innovations during recessions, respectively. Taking up one implication made for Chapter 2: In attempting to generate the highest social return of public innovation support, governments may should particularly focus on supporting the development of new products in SMEs and process/organisational innovations in large firms during recession periods. This means, they may have to be (more) selective to which type of firms and technologies they allocate public innovation support in general and additional counter-cyclical support in particular. Therefore, a well-designed innovation support program may lead to less employment losses and more innovativeness during recession periods. This probably leads to more sustainable growth in an economy.

Chapter 5 contributes to the discussion about the start-ups' ability to create jobs by investing in R&D activities. In general, the results imply that new firms should invest more in R&D to grow faster, which should also increase the chance of firm survival. Hence, research-oriented start-ups seem to be more successful than start-ups that do not conduct R&D activities. Further, start-ups should specifically invest in R&D during recession periods as it translates into an additional job-creating effect. Hence, it seems to be a beneficial strategy for the new firms to invest counter-cyclically in order to exploit new growth opportunities afterwards. This implication particularly holds for start-ups of the manufacturing sector. The positive counter-cyclical effect for Germany, however, only appears for the level but not for the direct increase of R&D investment. This implies that having a higher research-intensity during recessions is generally positively related to subsequent employment growth. It further implies that a positive (annual) deviation of the R&D level is rather ineffective in terms of job creation. Hence, the firms should try to maintain a relatively high but stable R&D investment level. The implication is a bit different for the US start-ups. In their case, the level of R&D investment does not play a significant role in their ability to create jobs. However, it is a beneficial strategy for the firms to directly increase their R&D investment during recession periods. As the US-American market for venture capital is much larger than the German one, it may be more feasible for US start-ups to get sufficient additional funding necessary to improve the development of new products, thus the firms' growth prospect. German start-ups typically have to rely on their own financial means, bank credits or public support in case they need an injection of capital. During a recession, it may be more difficult to get additional funding than in the US because the founders' own wealth is very likely to deteriorate as is the bank lending. From a policymaker's perspective, this indicates a need for public R&D support of German start-ups particularly during recession periods. As we have seen in Chapter 2, an R&D subsidy program during a recession may not be an effective way to support SMEs' R&D investment. Instead, support possibilities may draw on publicly financed venture capital funds that are a common type of venture capital funds in Germany (Röhl, 2014). Providing those types of funds with more capital particularly during recessions can have positive effects on the start-ups' R&D investment. In addition to the financial support, VC funds also provide management assistance and networks that may facilitate research cooperation and finding new investors, respectively. Unfortunately, our data did not allow us to investigate the effects of R&D on start-up growth from the founding year on but only from the start-ups' third/fourth year of existence on. Nevertheless, it is likely that R&D investment – from the beginning on – has a positive effect on the firms' employment growth. This would mean that public policies aiming at encouraging potential entrepreneurs to found research-oriented businesses could be beneficial for the economy in terms of employment growth. This may be particularly true for start-ups founded during recession periods when labour demand cools off and labour supply increases, respectively. In this sense, young firms can hire new employees more easily, which may allow them to generate higher sales in the following boom period. Hence, from a policymaker's point of view it may be also worth to establish/strengthen public venture capital funds during recessions.

6.4 Limitations and suggestions for future research

There are several general limitations restricting the conclusions that can be drawn from this thesis' research chapters. That is, it is difficult to derive general conclusions about the particular relationship between the business cycle, firm innovation and firm growth. In this respect, the first limitation refers to the different types of firms that were included in the different chapters' analyses. Chapter 2 focussed on SMEs, Chapter 3 did not distinguish between any size classes and Chapter 5 focussed on start-ups only. The study presented in Chapter 4 is the only one that investigated effects for a general firm sample and also for SMEs and large firms separately. This opens up possibilities for future research in that the business cycle dependency of the particular relationships can be analysed for firms of the same size class or of the same age cohort. Future analyses may also benefit from examining the effects for firms of the same industry class. There are potentially structural differences, for instance, between manufacturing and service firms in the type of innovations targeted and in the way innovations affect the firms' performance, respectively. This may be particularly relevant against the backdrop of public R&D support schemes as probably only few and specific types of service firms apply for that type of funding as compared to manufacturing firms.

The second limitation concerns the strong focus on Germany. Despite Chapter 4 focussed on firms of different European countries and Chapter 5 compared effects between German and US start-ups, a large part of the thesis centred on German firms and Germany's growth pattern of the years 2006-2012. This pattern was rather atypical for Germany but also as compared to other industrialised economies. That is, in 2009 Germany suffered from the deepest recession of the post-war era before having experienced a very strong and short recovery period in 2010. To be able to make more generalisable conclusions, future research should investigate a longer time period that also includes more moderate recession years like the ones from the beginning of this millennium. In addition, it would be necessary to examine the effects found in the respective chapters for other important economies like China or the USA as countries are heterogeneous in terms of the type and quality of innovations.

Another limitation relates to the fact that the particular channels linking R&D investment with firm growth were analysed separately. In principle, firm-level innovation and growth is one complex the analysis of which would typically benefit from modelling the firms' innovation decisions and the corresponding effect on employment growth altogether. The main drawback of such an analysis is that the empirical implementation would require a homogeneous firm sample that includes many instruments (exclusion restrictions). The fourth limitation refers to the short-term effects of innovation performance and employment growth on innovation in- and output, respectively, we investigated. While this is not an issue in Chapter 2 and not a serious problem in Chapter 4, it may be a concern in Chapter 3 and Chapter 5. The latter two examine a one-year lag between innovation investment and firm or innovation performance. In principle, it takes some more time than one year for innovation investment to take full effect on firms as the investment has to be transformed in new products/processes first. However, this means that we probably underestimate the respective effects. Future research can build on this and use longer lags.

6.5 Concluding remarks

Despite the above limitations, the research presented in this dissertation contributes to the literature primarily by shedding some light on the efficacy of firms' innovation activities over the business cycle. In particular against the backdrop of an increasing focus on innovation policy among the world's economies, advancing the understanding of how innovation affects growth is essential. For this reason, it is important to investigate and to compare the underlying relationships for different countries. If only in part, this thesis put this into research practice. The findings of the studies imply that it makes a difference in terms of firm performance whether or not firm-level innovation and public support programs are conducted pro- or counter-cyclically.

Nederlandse Samenvating

Om diepe recessies te voorkomen en periodes van sterke expansie te creëeren is het essentieel de mechanismes te begrijpen achter economische groei op lange termijn. Innovatie is de sleutel tot die economische groei. Het vergroot de kennisbasis en leidt tot technologische verandering en productiviteitsgroei. Belangrijke economische regios zoals China, Europa en de VS hebben op innovatie gebaseerde plannen geïnitieerd. Beleidsmakers zijn zich dus sterk bewust van het belang van innovatie. Het feit dat innovatie economische groei op lange termijn bepaalt, betekent echter niet dat innovatie onafhankelijk is van conjuncturele schommelingen. Het kan zeer duur zijn om nieuwe producten te ontwikkelen, zeker als die onderzoeksintens zijn. Daarom kan het makkelijker zijn om ze te financieren in periodes van economische groei. Ook kan het succes van innovaties, zoals de verkoop van nieuwe producten, groter zijn wanneer de economie groeit. Daarom moet een goed ontworpen innovatiestrategie rekening houden met de onderliggende conjunctuurdynamieken. Bestaand economisch onderzoek over de conjunctuurafhankelijkheid van innovatie heeft zich echter primair gefocust op (i) investering in innovatie en (ii) de timing van innovatie.

Deze thesis gaat een stap verder en presenteert het eerste empirisch bewijs voor de werkzaamheid van innovatie op ondernemingsniveau over de conjuntuurcyclus heen. Hoofdstuk 2 onderzoekt de impact van publieke O&O-subsidies op de O&O-investeringen van MKB-bedrijven in de meest recente economische crisis in Duitsland. Hoofdstuk 2 vindt dat publieke O&O-financiering een positief effect had op de grootte van O&O-investeringen van MKB-bedrijven. Bovendien toont het hoofdstuk een crowding out effect aan van O&O-subsidies voor het crisisjaar 2009. Dat betekent dat de O&O-investeringen van gesubsidieerde bedrijven lager waren dan die voor niet-gesubsidieerde bedrijven in 2009. Na de crisis, wanneer het Duits BNP in 2010 bijna het niveau van voor de crisis bereikt had, veroorzaakten subsidies weer een addionaliteitseffect. Maar dit was kleiner dan het additionaliteitseffect van de pre-crisis jaren. Bijkomende tests geven aan dat deze tijdelijke crowding out veroorzaakt werd door terughoudendheid van innovatieinvesteringen door gesubsidieerde bedrijven, en niet door het anticyclisch innovatiebeleid van Duitsland. De resultaten suggereren dat publieke O&O-subsidies voor MKB-bedrijven de gewenste additionaliteitseffecten veroorzaken, maar dat een anticyclisch steunschema voorzichtig ontworpen moet worden.

Het volgende hoofdstuk behandelt de link tussen de aanpassing van innovatieinvesteringen en de prestatie van productinnovaties en de afhankelijkheid daarvan van de conjunctuurcyclus. Het onderzoekt of bedrijven die hun innovatieuitgaven verhoogden tijdens het dieptepunt van de laatste crisis de prestaties van hun productinnovaties konden verbeteren. Het hoofdstuk toont aan dat procyclische innovatieaanpassingen een positief effect hebben op innovatiesuccess erna. Deze relatie geldt voor industrie-gebaseerde en BNP-gebaseerde indicatoren. Daarenboven vindt het hoofdstuk dat anticyclische innovatieaanpassingen een effectieve manier zijn om innovatieprestaties te verbeteren. Het positieve anticyclische effect is zelfs sterker dan het overeenstemmende procyclische effect. Hoofdstuk 4 betreft de waarschijnlijk meest relevante relatie in de context van innovatiebeleid: het effect van innovatie op werkgelegenheidsgroei. Het hoofdstuk onderzoekt de werkgelegenheidsgroeieffecten van verschillende types van innovaties over de conjuctuurcyclus. Het specifiek doel is de mogelijke veerkracht te onderzoeken van innovatoren als ze met een economische malaise worden geconfronteerd. De analyse is gebaseerd op de Europa-wijd uitgevoerde Community Innovation Survey (CIS) en behelst productiebedrijven in 26 Europese landen. Hoofdstuk 4 presenteert vier bevindingen. Ten eerste is het netto tewerkstellingsgroeieffect van productinnovaties procyclisch. Het blijkt positief te zijn in alle conjunctuurfasen, behalve de recessiephase. Dus is het arbeidscreërend effect groter dan het mogelijke arbeidsvernietigende effect in iedere conjunctuursfase behalve als bedrijven een recessie tegemoet moeten gaan. Ten tweede hebben productinnovaties een tewerkstellingsbewarend effect in een economische malaise. Dit maakt innovatoren bestendiger dan bedrijven die geen productinnovaties geïntroduceerd hebben (niet-product innovatoren). Maar productinnovatoren schrappen gemiddeld gezien nog altijd banen tijdens recessies. Ten derde is deze bestendigheid van productinnovatoren enkel te vinden onder MKB-bedrijven, en niet in grote bedrijven. Ten vierde hebben product- en organisatieinnovaties de neiging om bedrijfswijde tewerkstellingsgroei te verminderen onder economische opleving en neergang. Dit heeft de implicatie dat stijgende productiviteitswinsten van oude producten de arbeidsvraag verdringen. Onze resultaten suggereren dat productinnovaties een belangrijke drijfveer zijn voor baancreatie op firma niveau. Ze kunnen zelfs banen beschermen tijdens periodes van negatieve groei.

Het laatste hoofdstuk van het onderzoek, hoofdstuk 5, focust op start-ups. Het onderzoekt het baanscheppend effect van O&O-investeringen van start-ups over de conjunctuurcyclus. Specifiek analyseren we of hogere O&O-investeringen tijdens de recessie van 2008/2009 hogere tewerkstellingsgroei onder start-ups teweeg heeft gebracht. Onze analyse is gebaseerd op twee vergelijkbare panel datasets die Duitsland en de VS betreffen. Onze resultaten geven aan dat de O&O-investeringen van start-ups de tewerkstellingsgroei van de firma's verhogen. Bijkomend vinden we dat anticyclische O&O-investeringen een effectieve manier zijn om tewerkstellingsgroei te verhogen. Maar dit anticyclisch effect is enkel significant voor productiebedrijven. Het verschil tussen de tewerkstellingseffecten van de steekproeven uit Duitsland en de VS is dat in de Duitse steekproef de O&O-intensiteit een anticyclisch effect prijsgeeft. Daartegenover is er in de VS steekproef het jaarlijks verschil in O&O-intensiteit als een significante anticyclische relatie tot tewerkstellingsgroei.

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Curriculum Vitae

Martin Hud was born on February 10, 1986, in Frankfurt(Oder), Germany. He moved to Berlin in January 1999 and attended the Ellen-Key-Schule, where he graduated in 2005. Subsequently, he studied Economics at Freie Universität Berlin and received his university degree (Diplom) in 2010. In his diploma thesis he analysed the monetary policy at the zero lower bound. After graduation, he made an internship at the Department of Industrial Economics of the German Institute for Economic Research (DIW) in Berlin. Following this, he was working as an intern at the Economics Department of the Kreditanstalt für Wiederaufbau (KfW) in Frankfurt am Main.

In April 2011, he joined the Department of Economics of Innovation and Industrial Dynamics at the Centre for European Economic Research (ZEW) in Mannheim as a researcher. Martin started his PhD at Maastricht University (Department of Organization and Strategy) in December 2011. From August 2012 to September 2012, he visited Professor Martin Carree at Maastricht University. Two years later, he visited Professor Hiroyuki Okamuro for three months, from March 2014 to June 2014, at Hitotsubashi University in Tokyo. Martin was also invited by Yuya Ikeda to visit the National Institute of Science and Technology Policy (NISTEP) in Tokyo in September 2016.